

Systematic Review

Smart Urban Agriculture in Transition: A Systematic Review of ICT Integration, Applications, and Challenges

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Abstract

This paper systematically reviews the emerging field of smart urban agriculture, defined as the integration of information and communication technologies (ICTs) into food production practices within and around built-up urban areas. Although urban agriculture and digital agriculture have each generated substantial scholarship, their intersection remains conceptually fragmented and empirically uneven. Following the PRISMA 2020 guidelines, this study reviews 143 English-language articles indexed in Web of Science and Scopus between 2016 and 2026, combining bibliometric mapping with structured thematic coding. The analysis shows that smart urban agriculture has expanded rapidly since 2021, but remains geographically concentrated and disciplinarily dispersed. Current research is organized mainly around IoT and sensor networks, machine learning, soilless cultivation, vertical farming, plant factories, and controlled-environment agriculture. ICT applications are most mature in enclosed, data-rich, and technically controllable systems, where they support monitoring, prediction, automation, and resource optimization. By contrast, community-based, open-space, and governance-oriented forms of urban agriculture remain underexplored. By systematically linking ICT families with different urban agriculture production settings, this review clarifies the field's emerging knowledge structure and demonstrates that technological development remains uneven across agricultural forms and socio-institutional contexts.



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Keywords: urban agriculture; information and communication technologies; internet of things; machine learning; controlled-environment agriculture; vertical farming

1. Introduction

Urban food systems are increasingly shaped by two interrelated transformations. The first is the growing pressure placed on agriculture by rapid urbanization, land use change, and rising food demand [1]. The second is the digital transformation of agriculture through information and communication technologies (ICTs) [2]. While these two trajectories have often been examined separately, their intersection has become increasingly important.

This paper refers to this intersection as smart urban agriculture: ICT-enabled agricultural practices located within and around built-up urban areas. Although this field has expanded rapidly in recent years, its conceptual boundaries, technological applications, and implementation challenges remain fragmented across different strands of literature.

Global urbanization has intensified the pressure on food systems. The United Nations projects that the global population will reach approximately 9.7 billion by 2050, with nearly 70% of people living in urban areas [3,4]. To meet future demand, food production may need to increase substantially, with estimates ranging from 59% to 98% [5]. At the same time, urban expansion continues to reshape land use patterns. Between 2003 and 2018, urban land area expanded by approximately 4%, while green space declined by 2% [6]. The conversion of agricultural and ecological land into urban infrastructure reduces local food production capacity, weakens ecosystem services, and increases the vulnerability of urban food systems. Urbanization, therefore, does not automatically improve food accessibility or food security [7]. Instead, it creates new challenges concerning how food can be produced, distributed, and governed within increasingly dense and resource-constrained urban environments.

Against this background, urban agriculture (UA) has been widely discussed as a potential pathway for strengthening urban food resilience and supporting more sustainable urban development. UA generally refers to the growing, processing, and distribution of food within and around urban areas [8]. It is associated with multiple objectives, including improving food access, shortening supply chains, enhancing urban ecological functions, and contributing to Sustainable Development Goals on Zero Hunger and on Sustainable Cities and Communities [9,10]. In practice, UA includes diverse forms such as rooftop farming, community gardens, vertical farming, hydroponics, aquaponics, aeroponics, and controlled-environment agriculture (CEA) [11–13]. These forms differ in scale, technology intensity, spatial requirements, ownership structure, and social purpose, but they share a common concern with re-embedding food production within urban and peri-urban spaces.

At the same time, agriculture is undergoing a significant digital transformation. Smart agriculture broadly refers to the application of digital technologies to agricultural production and management in order to improve monitoring, decision-making, resource efficiency, and automation. It has evolved from early precision agriculture into a data-driven paradigm described through related terms such as “Agriculture 4.0,” “digital agriculture,” and “smart farming” [14,15]. A wide range of technologies underpin this transformation. The Internet of Things (IoT) enables the collection of real-time data from agricultural environments [16]. Artificial intelligence (AI) and machine learning (ML) support predictive analytics for crop health, yield estimation, irrigation, pest detection, and resource allocation [17,18]. Geographic information systems (GIS) and remote sensing contribute to spatial analysis, land suitability assessment, and environmental monitoring. Robotics and automation can also reduce labor requirements and improve operational efficiency, particularly in controlled and spatially constrained environments. The declining cost of sensors, the expansion of cloud computing, and the maturation of open-source AI frameworks have further lowered the threshold for applying ICTs to agricultural production [19,20].

The convergence of UA and ICT has given rise to smart urban agriculture. However, smart urban agriculture should not be understood simply as the transfer of rural precision-agriculture technologies into cities. Urban environments generate distinctive conditions for agricultural innovation, including land scarcity, fragmented property rights, high energy and infrastructure costs, complex regulatory frameworks, and diverse stakeholder interests. They also create specific opportunities, such as proximity to consumers, access to urban data infrastructures, integration with buildings and circular-economy systems, and the possibility of linking food production with education, community development, and urban

resilience. Smart urban agriculture is therefore a distinct research domain shaped by the interaction between digital technologies and the spatial, social, ecological, and institutional conditions of cities [21,22].

Despite growing scholarly interest, the existing literature remains fragmented in three important respects. First, existing reviews have not fully captured the rapid technological developments that have occurred since the mid-2010s, particularly the growing use of IoT, AI, ML, automation, and data-driven monitoring systems in urban agricultural settings. Second, studies of urban agriculture and studies of smart agriculture often remain separated. Research on UA tends to emphasize food security, community benefits, land use, sustainability, and urban resilience, whereas research on smart agriculture tends to focus on rural production systems, precision farming, and technological performance. As a result, the specific intersections between ICTs and urban agricultural practices remain insufficiently synthesized. Third, there is still limited systematic understanding of how mature this research field is, which technologies are most commonly applied, which forms of UA are most frequently studied, and what barriers continue to constrain wider adoption.

To address these gaps, this paper conducts a systematic review of literature indexed in Web of Science and Scopus from 2016 to 2026, following the PRISMA 2020 guidelines. The review is structured around three research questions:

RQ1: What are the conceptual foundations, publication trends, and major research themes of smart urban agriculture?

RQ2: What smart technologies are most commonly used in urban agriculture, and how are they applied across different types of urban agriculture?

RQ3: What are the major barriers to the wider adoption of smart urban agriculture, and what research gaps remain?

This paper makes three contributions. First, it clarifies the conceptual foundations of smart urban agriculture by situating it at the intersection of UA and ICT-enabled agricultural transformation. Second, it provides a systematic overview of publication trends, research themes, technological applications, and agricultural types in the existing literature. Third, it identifies the key technical, economic, institutional, and social barriers that continue to limit the wider adoption of smart urban agriculture, thereby outlining priorities for future research.

The remainder of the paper is organized as follows. Section 2 reviews the conceptual foundations of urban agriculture, the evolution of ICT in agriculture, and the limitations of existing reviews. Section 3 explains the review methodology. Section 4 presents the bibliometric overview and addresses RQ1. Section 5 examines the application of ICTs across different types of urban agriculture and addresses RQ2. Section 6 discusses current progress, key barriers, and future research directions in response to RQ3. Section 7 concludes the paper.

2. Literature Review

This section establishes the conceptual basis for the subsequent systematic review. Section 2.1 reviews the concept and typology of urban agriculture. Section 2.2 traces the evolution of ICT in agriculture. Section 2.3 critically examines existing review literature in order to clarify the positioning and contribution of the present study.

2.1. Conceptual Foundations and Typology of Urban Agriculture

Urban agriculture is not a new phenomenon. Food cultivation within and around cities can be traced back to ancient urban gardens and, more recently, to twentieth-century “victory gardens”. What has changed, however, is its conceptual framing. Contemporary scholarship no longer treats UA as a residual or marginal agricultural activity within the

city, but increasingly understands it as a deliberate and multifunctional intervention in urban food systems [9,23].

Mougeot's [23] widely cited definition conceptualizes UA as a set of productive activities located within or on the fringe of urban settlements, using urban and peri-urban resources, products, and services to produce, process, and distribute food and non-food products. Similarly, FAO [9] emphasizes that UA includes both intra-urban and peri-urban practices. This peri-urban dimension is particularly important, as land at the urban fringe is often exposed to strong development pressure and conversion into built-up areas [7,22]. UA should therefore be understood not only as food production inside cities, but also as a spatially embedded practice shaped by the relationship between urban expansion, land use competition, and food system restructuring.

The defining characteristic of UA is its embeddedness in urban space and urban society. This embeddedness has three major implications. First, UA is highly heterogeneous in form. Specht et al. [12] and Al-Kodmany [13] identify a wide spectrum of practices, ranging from soil-based community gardens and allotments to building-integrated agriculture, including rooftop greenhouses and productive facades. At the more technologically intensive end of this spectrum are controlled-environment systems, such as vertical farms and plant factories with artificial lighting (PFALs). Despommier's [11] proposal for multi-story vertical farming popularized the idea of "growing upward rather than outward", stimulating extensive research on controlled indoor production. Soilless cultivation methods, including hydroponics, aquaponics, and aeroponics, are also prominent in urban contexts where land is scarce and soil quality is uncertain [21,24].

Second, UA operates under spatial and social constraints that differ fundamentally from those of rural agriculture. Urban land tenure is often unstable, soils may be contaminated, water access is mediated through municipal infrastructure, and agricultural activities are embedded in dense regulatory and social environments [22,25]. These conditions shape not only which forms of UA are feasible, but also which technologies are appropriate and socially acceptable. ICT solutions developed for large-scale rural fields cannot be directly transferred to urban contexts, where production spaces are often small, fragmented, vertically layered, and socially diverse [21].

Third, UA is multifunctional. Beyond food production, it can contribute to ecological objectives, such as urban cooling, biodiversity enhancement, and stormwater management; social objectives, such as community building, education, and food justice; and economic objectives, such as local employment and shorter food supply chains. This multifunctionality means that the value of UA cannot be assessed solely through conventional agricultural metrics such as yield per unit area. Goldstein et al. [25] and Orsini et al. [10] note that in high-income cities, environmental and social benefits often dominate the justification for UA, whereas in rapidly urbanizing low- and middle-income regions, food security concerns are usually more prominent.

Taken together, the literature suggests that UA is best understood as a diverse and multifunctional set of practices shaped by urban spatial conditions, social demands, and institutional contexts. This understanding is important for the present review because the application of ICT in UA is not technologically neutral. Different UA types, such as community gardens, rooftop farms, vertical farms, hydroponic systems, aquaponics, and controlled-environment agriculture, create different technological requirements, operational constraints, and evaluation criteria. A systematic review of smart urban agriculture therefore needs to examine not only which technologies are used, but also how they are adapted to different forms and functions of UA.

2.2. The Evolution of ICT in Agriculture

The use of ICT in agriculture has evolved through several partially overlapping stages, moving from site-specific field management to data-driven and increasingly integrated production systems. The first major stage was precision agriculture, which emerged in the 1980s and 1990s alongside the diffusion of GPS, variable-rate application technologies, and yield monitors. Its central objective was to manage within-field variability at a finer spatial resolution than conventional uniform field-level treatment allowed. This marked an important conceptual shift: agricultural land was no longer treated as a homogeneous production unit, but as a spatially differentiated environment requiring targeted monitoring and management [14,26].

A second stage, often described through terms such as “Agriculture 4.0,” “digital agriculture,” or “smart farming,” broadened the focus from spatial precision to data-driven agricultural management. In this phase, sensing, computation, communication, and control became increasingly integrated within cyber-physical production systems. Wolfert et al. [26] define smart farming as the application of ICT in agriculture, supported by technologies such as the Internet of Things, cloud computing, and machine learning across processes of planning, monitoring, control, and analysis. Saiz-Rubio and Rovira-Más [14] further argue that contemporary smart farming has shifted toward “integrated crop data management,” in which heterogeneous data streams are combined to generate actionable insights. Similarly, Wolfert et al. [26] emphasize that the rise of big data has transformed precision agriculture into an increasingly information-driven enterprise.

A third and more recent development is the growing importance of AI-enabled and connected farming systems. The Internet of Things and wireless sensor networks turn physical elements of agricultural production, such as soil, water, crops, machinery, and growing environments, into networked data sources [16,20]. Machine learning and deep learning techniques are then used to translate these data into predictions, classifications, and decision-support outputs, including crop health diagnosis, yield estimation, pest detection, irrigation scheduling, and resource optimization [17,18]. Fuzzy logic, first introduced by Herman and Surantha [27], has also remained relevant as a method for handling uncertainty in agronomic decision-making, particularly in irrigation, fertilization, and greenhouse control systems, often in combination with neural networks [28].

These technological developments should not be understood as separate or mutually exclusive trajectories. In practice, contemporary smart agricultural systems often combine multiple technologies within integrated architectures. Vallejo-Gómez et al. [28], for example, show that smart irrigation systems frequently integrate IoT sensing, machine learning, and fuzzy logic. Siregar et al. [21] similarly identify a layered architecture in vertical farming, where IoT-based sensing feeds AI-driven analytics, which in turn supports automated control. The broader trend is therefore not the replacement of one technology by another, but the shift from isolated digital tools toward multi-technology systems that connect data collection, analysis, decision-making, and operational control.

Two enabling developments are particularly important for the wider diffusion of ICT in agriculture. First, sensors, microcontrollers, and low-cost computing devices, including Arduino, ESP32, and Raspberry Pi, have become more accessible, while cloud and edge computing platforms have become increasingly available [19,28]. These developments have lowered the technical and financial barriers to small-scale ICT deployment. Second, open-source AI frameworks and more accessible datasets have reduced the threshold for developing and adapting data-driven applications [15]. As a result, ICT is no longer confined to large-scale rural production systems or capital-intensive precision farming. It is increasingly applicable to smaller, more controlled, and spatially constrained agricultural settings.

This evolution is directly relevant to urban agriculture. Many forms of UA, especially rooftop farming, hydroponics, aquaponics, vertical farming, and controlled-environment agriculture, depend on the precise monitoring and regulation of growing conditions. At the same time, they often operate at smaller scales and within more complex built environments than conventional rural agriculture. The evolution of ICT from field-based precision tools to integrated, sensor-based, and AI-supported systems has therefore created the technological basis for smart urban agriculture. However, whether these technologies can be effectively adapted to urban settings depends not only on technical performance, but also on cost, usability, infrastructure, regulatory conditions, and the specific type of urban agriculture involved.

2.3. Limitations of Existing Reviews and the Positioning of This Study

Although research on both smart agriculture and urban agriculture has expanded rapidly, existing reviews have generally examined these two trajectories in parallel rather than at their intersection. Reviews of smart agriculture tend to focus on digital technologies, algorithms, data architectures, or specific management functions, while reviews of urban agriculture tend to emphasize food security, sustainability, spatial form, or social benefits. As a result, the specific ways in which ICTs are applied to different forms of urban agriculture remain insufficiently synthesized. Table 1 summarizes several major review articles relevant to the present study and highlights their scope and limitations.

Table 1. Major review articles related to smart agriculture and urban agriculture (source: authors).

Review	Scope and Focus	Relevance and Limitations for This Review
Wolfert et al. [26]	Big data in smart farming, including technological landscapes, data value chains, and business models	Provides an important foundation for understanding data-driven agriculture, but the empirical focus is mainly on large-scale agribusiness and supply-chain contexts. Urban and peri-urban agricultural settings receive limited attention.
Liakos et al. [17]; Kamilaris and Prenafeta-Boldú [18]	Applications of machine learning and deep learning in agriculture, including crops, water, soil, livestock, and image-based tasks	Offers detailed accounts of algorithmic applications, but remains largely neutral regarding deployment contexts. Differences between rural and urban settings, production scales, infrastructure conditions, and user groups are not systematically examined.
Vallejo-Gómez, Osorio and Hincapié [28]	Smart irrigation systems integrating AI, IoT, and fuzzy logic	Demonstrates the integration of multiple technologies in irrigation systems, but focuses on irrigation as a specific function. Urban agriculture appears only as a limited subset of the reviewed studies, indicating that urban smart irrigation remains underexplored.
Siregar et al. [21]	Applications of AI, ML, DL, and IoT in vertical farming	Directly addresses a technologically intensive form of urban agriculture, but is limited to vertical farming. Other forms of UA, such as community gardens, rooftop farms, hydroponics, aquaponics, and peri-urban production, are not systematically covered.
Ng and Maheswaran [22]	Emerging and disruptive technologies in urban agriculture, including IoT, AI, robotics, blockchain, and digital twins	Provides broad technological coverage and is highly relevant to smart urban agriculture, but does not offer a PRISMA-style systematic review or bibliometric mapping. Technologies are discussed mainly as discrete options rather than as integrated socio-technical systems.

The existing review literature reveals three main limitations. First, current reviews remain limited in integrative scope. Most reviews are often bounded by a specific technological

function, such as irrigation [28], a specific UA form, such as vertical farming [21], or a specific technology family, such as machine learning or deep learning [17,18]. These studies provide valuable insights within their respective domains, but they offer limited understanding of how technologies, urban agricultural forms, and functional objectives are combined in practice. As a result, their findings are difficult to integrate into a broader account of smart urban agriculture as a distinct research field.

Second, the literature lacks sufficient methodological systematicity at the intersection of UA and ICT. Broad reviews of emerging technologies in UA, such as Ng and Mahkeswaran [22], provide useful conceptual and technological overviews but do not employ PRISMA-style screening or bibliometric mapping. Conversely, reviews that adopt systematic procedures often focus on a narrower technological domain or a single agricultural function. Few studies combine methodological rigor with broad coverage across different UA forms and ICT applications.

Third, the maturity and structure of the field have rarely been assessed. The reviews summarized in Table 1 seldom treat smart urban agriculture as an independent field of inquiry. Consequently, they do not systematically examine its publication trajectory, dominant research themes, geographical distribution, technological composition, or the balance between conceptual, experimental, and applied studies. Without such an assessment, it remains difficult to determine whether the field is consolidating around shared concepts and methods, or whether it remains fragmented across separate bodies of literature.

Together, these limitations define the research space occupied by the present study. This review treats the intersection of UA and ICT as the unit of analysis in its own right. It combines a PRISMA-guided systematic review with bibliometric mapping, while moving beyond any single technology, function, or form of UA. In doing so, the paper examines smart urban agriculture through three interconnected dimensions: the conceptual and thematic development of the field, the application of ICTs across different UA types, and the barriers that continue to constrain wider adoption. This positioning allows the review to clarify not only what technologies are being used, but also where, how, and under what conditions they are applied in urban agricultural contexts.

3. Methodology

A systematic review was adopted to identify, screen, and synthesize the dispersed literature on smart urban agriculture. This approach is particularly suitable for an emerging and interdisciplinary field, where relevant studies are distributed across agricultural science, urban studies, environmental science, engineering, computer science, and sustainability research. The review followed the PRISMA 2020 framework, which provides a transparent and replicable procedure for reporting literature identification, screening, eligibility assessment, and final inclusion.

3.1. Identification

Scopus and Web of Science were selected as the primary bibliographic databases for this review. Both databases provide broad coverage of peer-reviewed literature across scientific, technological, environmental, and interdisciplinary fields, making them appropriate for a topic that connects urban agriculture with ICT-enabled agricultural innovation. Using both databases also helps reduce the risk of database-specific bias, as relevant studies may be indexed in one database but not the other.

The search strategy was designed to identify studies located at the intersection of two conceptual domains: urban agriculture and ICT-enabled agricultural technologies. The first group of search terms captured urban agriculture and its major production forms, including urban farming, peri-urban agriculture, vertical farming, rooftop farming, indoor

farming, hydroponics, aquaponics, urban greenhouses, and controlled-environment agriculture. The second group captured digital and smart technologies, including the Internet of Things, artificial intelligence, machine learning, deep learning, neural networks, computer vision, sensor networks, wireless sensors, smart monitoring, digital twins, big data analytics, robotics, blockchain, GIS, and remote sensing.

The Scopus search string was as follows:

TITLE-ABS-KEY(

("urban agriculture" OR "urban farming" OR "peri-urban agriculture"
OR "vertical farm*" OR "rooftop farm*" OR "indoor farm*"
OR hydroponic* OR aquaponic* OR "urban greenhouse*"
OR "controlled environment agriculture")

AND

("Internet of Things" OR IoT OR "artificial intelligence"
OR "machine learning" OR "deep learning" OR "neural network*"
OR "computer vision" OR "image recognition" OR "sensor network*"
OR "wireless sensor*" OR "smart monitoring" OR "precision monitoring"
OR "digital twin*" OR "big data analytics" OR robotics
OR blockchain OR GIS OR "geographic information system*"
OR "remote sensing")

)

AND NOT TITLE-ABS-KEY(

livestock OR fisheries OR poultry OR "field crop*" OR rangeland OR pasture

)

AND PUBYEAR > 2015

AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "re"))

AND (LIMIT-TO (LANGUAGE, "English"))

The corresponding Web of Science search string was:

TS = (

("urban agriculture" OR "urban farming" OR "peri-urban agriculture"
OR "vertical farm*" OR "rooftop farm*" OR "indoor farm*"
OR hydroponic* OR aquaponic* OR "urban greenhouse*"
OR "controlled environment agriculture")

AND

("Internet of Things" OR IoT OR "artificial intelligence"
OR "machine learning" OR "deep learning" OR "neural network*"
OR "computer vision" OR "image recognition" OR "sensor network*"
OR "wireless sensor*" OR "smart monitoring" OR "precision monitoring"
OR "digital twin*" OR "big data analytics" OR robotics
OR blockchain OR GIS OR "geographic information system*"
OR "remote sensing")

)

NOT TS = (livestock OR fisheries OR poultry OR "field crop*" OR rangeland OR pasture)

Limits: Document Type = Article OR Review; Publication Year = 2016–2026; Language = English

The Web of Science results were limited to articles and review articles published in English between 2016 and 2026. The same publication-year, document-type, and language restrictions were applied in Scopus. The search was executed on 23 May 2026. It returned

1121 records from Scopus and 896 records from Web of Science, yielding an initial corpus of 2017 records for subsequent duplicate removal and screening. The review period was set to 2016–2026 because the intersection of ICTs and urban agriculture began to emerge as a distinct and rapidly growing research area only in the mid-2010s; a small number of earlier, isolated studies were not sufficient to support systematic bibliometric or thematic analysis, and 2016 marks the point from which annual output became continuous.

3.2. Screening, Eligibility, and Inclusion

Following the initial retrieval of 2017 records, title- and metadata-based deduplication removed 772 duplicate entries, leaving 1245 unique records for screening. The titles, abstracts, and author keywords of these records were then examined against four inclusion criteria defined in accordance with the conceptual scope of this review. Each record was assessed manually. Where the eligibility of a record could not be determined on the basis of its title and abstract, it was retained for full-text inspection rather than excluded at this stage.

First, the study had to have an explicit urban or peri-urban setting. The research object had to be situated within built-up urban areas or peri-urban areas, with agricultural activities embedded in an urban spatial context. Operationally, eligible studies were those conducted at the urban, district, community, building, or urban-fringe scale, or those that explicitly engaged with urban spatial constraints, urban land use dynamics, or urban food systems. Studies conducted purely in rural areas or at the conventional field scale were excluded. Nationwide remote sensing classifications were also excluded where they did not distinguish urban or peri-urban agricultural contexts from rural agricultural land.

Second, the study had to have a food production orientation. The agricultural activity under examination had to involve the cultivation, processing, or distribution of edible crops or food products in at least one stage. Food production did not need to be the sole objective of the study; technical, spatial-analytical, and policy-oriented studies were retained where an edible crop or food production system formed part of the research object. Studies concerned exclusively with ornamental greening, biodiversity, carbon sequestration, landscape design, or non-edible crops were excluded.

Third, the study had to involve the substantive application of ICT. Eligible studies were required to deploy, design, test, model, or evaluate at least one ICT-enabled technology, rather than merely mentioning such technologies in passing. Eligible technologies included, but were not limited to, the Internet of Things and sensor networks, artificial intelligence and machine learning, computer vision, GIS and remote sensing, digital twins, big-data analytics, robotics, automation, and blockchain, provided that the technology performed an analytical, monitoring, control, optimization, or decision-support function. Studies that referred to ICT only prospectively in the introduction or conclusion, without implementation, modeling, or empirical analysis, were excluded.

Fourth, the study had to provide sufficient methodological transparency. For empirical and original technical studies, the article had to report enough methodological detail to allow extraction of the ICT used, the problem addressed, the implementation approach, and the main results. This included, where relevant, descriptions of data sources, model structures, system architectures, experimental settings, or evaluation metrics. Purely conceptual frameworks, policy commentaries, and vision-oriented articles lacking technical implementation or empirical grounding were excluded from the analytical corpus. Review articles were retained as background references where relevant, but were not included in the structured coding or quantitative synthesis.

Two interpretive conventions were established to ensure consistency in applying the urban-setting criterion. First, studies explicitly framed around recognized urban agriculture

forms, including urban agriculture, vertical farming, plant factories, rooftop farming, community gardens, building-integrated agriculture, and peri-urban agriculture, were treated as satisfying the urban-context requirement. Second, studies of soilless or controlled-environment systems, including hydroponics, aquaponics, aeroponics, greenhouses, and controlled-environment agriculture, were retained only when the text provided explicit urban framing, such as references to urban food systems, urban settings, food miles, local food supply, or spatial constraints associated with cities. This distinction was necessary because such systems are also common in rural, commercial, or laboratory contexts.

Through title and abstract screening, 1039 of the 1245 unique records were excluded, leaving 206 records for full-text assessment. Full-text screening then excluded a further 82 records that did not meet the inclusion criteria upon closer inspection. The remaining 124 eligible records were supplemented by 19 additional articles identified through backward and forward reference checking and targeted searches of relevant journals. This resulted in a final analytical corpus of 143 studies. The complete selection process is presented in the PRISMA 2020 flow diagram in Figure 1. The completed PRISMA checklist is provided as Supplementary Table S1.

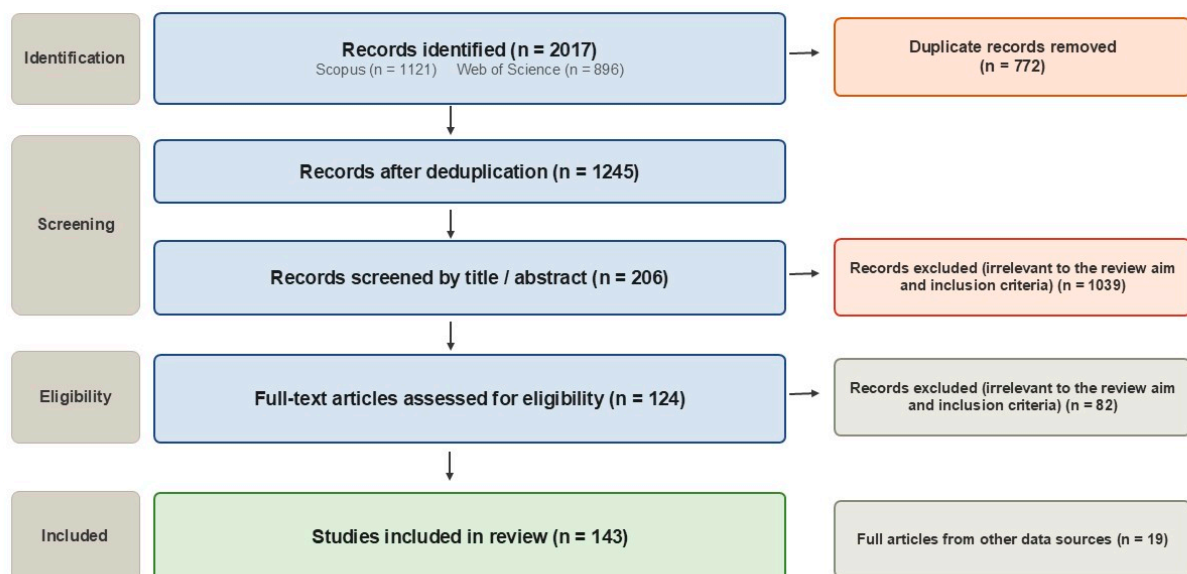


Figure 1. The retrieval of eligible studies by the PRISMA flowchart (source: authors).

3.3. Structured Data Extraction and Coding

For each study included in the final analytical corpus, a structured set of fields was extracted to support the subsequent quantitative and thematic synthesis. Two coding axes were applied to every study: the ICT family employed, and the scenario (urban agriculture production system) in which it was applied. Both axes are multi-label, so a study may be assigned to more than one category on either axis. Urban agriculture scenarios included, for example, community gardens, rooftop and building-integrated agriculture, vertical farming, soilless cultivation (hydroponics, aquaponics, aeroponics), greenhouses and controlled-environment agriculture, plant factories, and peri-urban open fields. ICT families included IoT and sensor networks, AI and machine learning, computer vision, GIS and remote sensing, digital twins and decision-support systems, robotics, and automation and control. The operational definition and decision rule for each category are given in Supplementary Table S3; the full list of the 143 reviewed studies is provided in Supplementary Table S2, and the complete study-level coding is provided in Supplementary Table S4.

Coding was carried out by three of the authors on the basis of the shared coding manual (Supplementary Table S3), which was jointly developed and finalized before full-

corpus coding began so that all three coders applied an identical rule set. Each study was read in full, and codes on both axes were assigned from its own methods and results rather than from its title, abstract, or keywords.

To check consistency in applying the manual, a subset of 37 studies (approximately 26% of the corpus) was independently double-coded by two authors, while the remaining studies were single-coded. The two independent codings of this subset were compared, and all disagreements were reconciled by consensus against the manual; recurrent boundary cases were used to clarify the manual so that the same rules were applied consistently to the single-coded studies.

3.4. Bibliometric and Keyword Co-Occurrence Analysis

Keyword co-occurrence analysis was performed using VOSviewer (version 1.6.20, Leiden University, The Netherlands). Author keywords were extracted from the 143 included publications. A thesaurus file was manually created to merge synonyms and unify term variants (e.g., “machine learning” and “ML” were merged into “machine learning”; “deep learning” and “DL” were merged into “deep learning”). Keywords that appeared in fewer than 3 publications were excluded from the analysis. The association strength normalization method was used to calculate keyword similarity. A relevance score was calculated for each keyword, and the top 60% of the most relevant terms were selected for visualization, resulting in a final set of 38 keywords. The VOSviewer clustering algorithm with a resolution parameter of 0.70 was applied to identify thematic clusters. This resolution value was chosen because the default setting of 1.00 produced 7 clusters with limited thematic differentiation, whereas the lower resolution of 0.70 yielded 6 more distinct and interpretable clusters without over-fragmenting the keyword network. For the temporal evolution analysis, an overlay visualization was generated based on the average publication year of keywords, with colors ranging from blue (earlier) to yellow (later).

In addition, the geographical distribution of the included studies was analyzed by extracting the corresponding author’s country of affiliation from each publication. A global map was created using GIS software (QGIS 3.44) to visualize the spatial distribution of the literature.

4. Research Landscape and Technological Context

This section addresses RQ1 by examining the publication profile, geographical distribution, knowledge structure, and thematic evolution of smart urban agriculture research. While Section 2 established the conceptual foundations of urban agriculture and ICT-enabled agricultural transformation, this section turns to the empirical corpus of 143 studies to assess how the field has developed in practice. The analysis proceeds in two steps. Section 4.1 provides a bibliometric overview of publication trends, journal outlets, and geographical distribution. Section 4.2 then uses keyword co-occurrence and temporal overlay analysis to identify the major knowledge domains and technological trajectories within the field. Together, these analyses clarify whether smart urban agriculture is emerging as a coherent research area, and where its current thematic and geographical limitations lie.

4.1. Publication Trends and Geographical Distribution

The final corpus comprised 143 studies on ICT-integrated urban agriculture. To provide an overview of the research landscape, Figure 2 summarizes three basic bibliometric dimensions: annual publication trends, journal distribution, and geographical distribution.

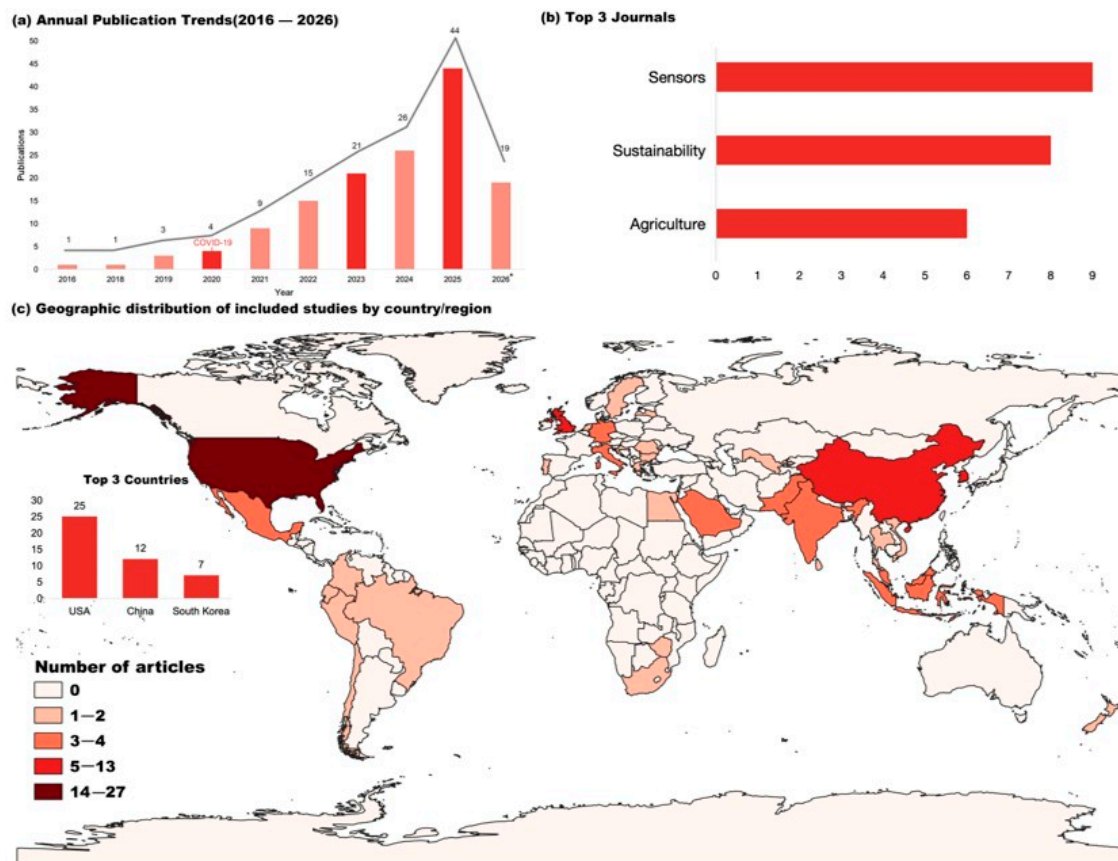


Figure 2. Bibliometric profile of smart urban agriculture research. (a) Annual publication trend of the included studies from 2016 to 2026; (b) top publishing journals; (c) geographical distribution of included studies by country or region (source: authors).

As shown in Figure 2a, research on smart urban agriculture has expanded rapidly since 2021. Annual output remained relatively low before 2020, suggesting that ICT-enabled urban agriculture was still a scattered and exploratory research topic during the early period. Publications then increased steadily, reaching the highest annual output in 2025. The partial count for 2026 should be interpreted cautiously, as the search was conducted on 23 May 2026 and therefore does not represent a full publication year. Overall, the temporal pattern indicates that smart urban agriculture has moved from a marginal intersection between urban agriculture and smart farming toward a more visible and rapidly expanding research area.

The journal distribution shown in Figure 2b indicates a dispersed but clearly interdisciplinary publication structure. The leading outlets were *Sensors* ($n = 9$), *Sustainability* ($n = 8$), and *Agriculture* ($n = 6$). These journals span sensing technologies, sustainability science, and agricultural engineering. The absence of a single dominant outlet suggests that smart urban agriculture has not yet consolidated around a clearly defined disciplinary home. Instead, the literature remains distributed across urban sustainability, agricultural technology, environmental science, and ICT-oriented research communities.

The geographical distribution shown in Figure 2c is more concentrated. The United States contributed the largest number of studies ($n = 25$), followed by China ($n = 12$) and South Korea ($n = 7$). Together, these three countries accounted for 44 studies, or approximately one-third of the final corpus. Beyond this group, most countries contributed only one to four publications, while large parts of Africa, Central Asia, Eastern Europe, and Latin America were weakly represented or absent. This pattern suggests that smart urban agriculture remains a geographically uneven research agenda. It is most visible in

countries where urban food system debates, technological capacity, controlled-environment agriculture, and research funding have already begun to converge.

This geographical imbalance is substantively important. Many regions facing severe pressures related to urban food security, climate adaptation, water scarcity, and land use competition have not yet produced a comparable research base on ICT-integrated urban agriculture. The current global literature therefore reflects not only where smart urban agriculture is being studied, but also where the institutional, technical, and financial capacity exists to frame urban food production as a data-driven and technologically manageable system. In this sense, Figure 2 reveals a field that is growing quickly, but remains unevenly developed across disciplines and regions.

4.2. Knowledge Structure and Technological Trajectories

Figure 3 presents the internal knowledge structure and temporal development of smart urban agriculture research based on keyword co-occurrence and temporal overlay analysis.

The keyword co-occurrence network in Figure 3a is organized around three highly connected terms: urban agriculture, Internet of Things, and hydroponics. These terms function as central nodes linking the urban, technological, and production-oriented dimensions of the field. Surrounding them are keywords such as vertical farming, machine learning, plant factory, and smart agriculture, which together form the principal knowledge structure of the literature. By contrast, keywords related to governance, planning, community participation, social equity, or food justice are largely absent from the network. This pattern suggests that existing research on smart urban agriculture is primarily organized around ICT-enabled production systems, rather than broader questions of urban food governance, spatial planning, or social inclusion.

The temporal overlay visualization in Figure 3b suggests a gradual shift in the technological focus of the field. Earlier studies were more strongly associated with sensors, remote sensing, indoor farming, and plant factories, indicating an initial emphasis on environmental monitoring and controlled production systems. Around 2023, the Internet of Things became a central bridging concept, linking data collection, connectivity, and agricultural management. Since 2024, keywords such as vertical farming, precision agriculture, deep learning, image processing, and automation have become more prominent. This shift indicates a movement from basic monitoring and data acquisition toward predictive analytics, intelligent decision support, and automated control.

Overall, the keyword analysis suggests that smart urban agriculture is developing along a trajectory from monitoring, to connectivity, and increasingly toward intelligence and automation. However, this trajectory remains selective. The dominance of hydroponics, vertical farming, plant factories, and controlled-environment agriculture indicates that ICT integration is currently concentrated in production systems that are technically controllable, data-rich, and suitable for automation. By contrast, less controlled forms of UA, such as community gardens, allotments, rooftop gardens, and peri-urban farming, appear less central in the current keyword structure. Similarly, the limited visibility of governance, planning, participation, and equity-related terms suggests that the social and institutional dimensions of smart urban agriculture remain underdeveloped. The field is therefore technologically dynamic, but still unevenly integrated across the wider spectrum of urban agriculture.

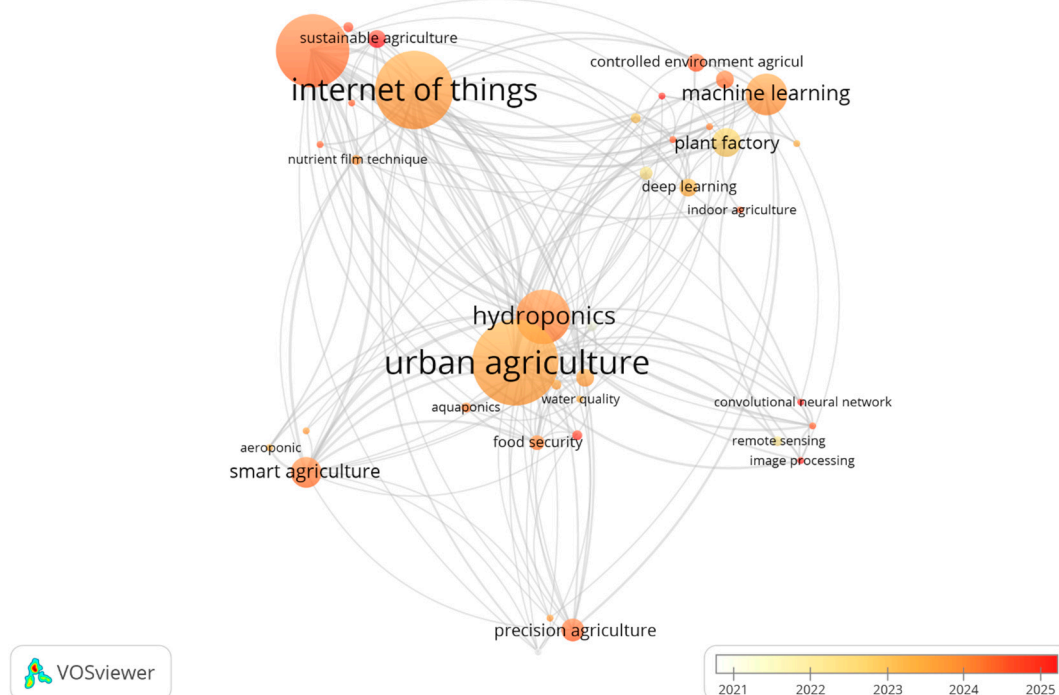
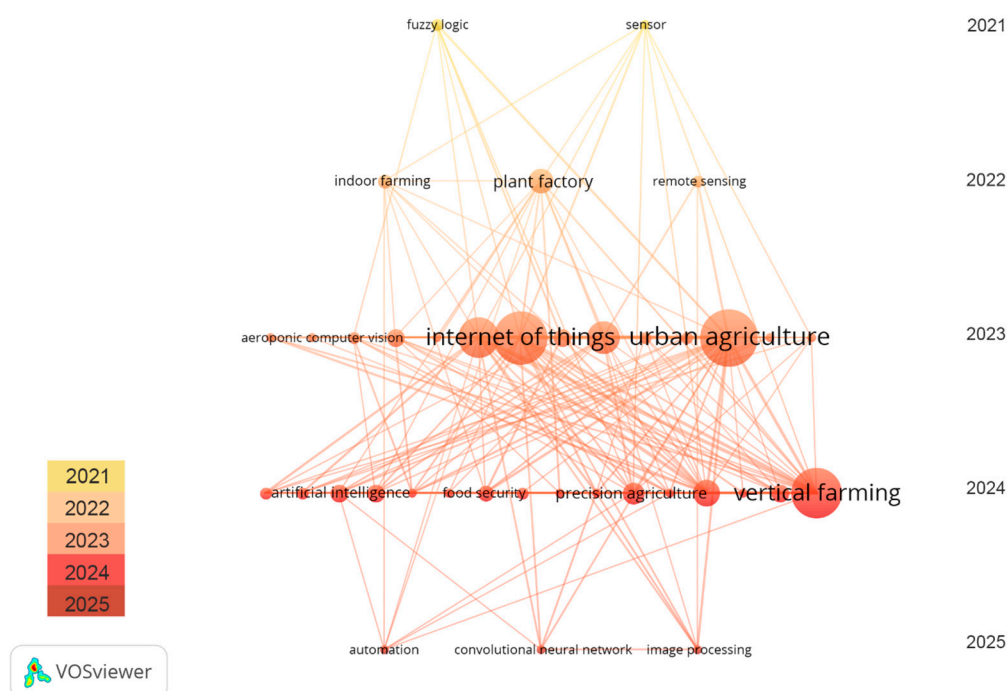
(a) Keyword co-occurrence network of the included literature**(b) Keyword-based visualization of technological evolution from 2021 to 2025**

Figure 3. Keyword co-occurrence and temporal evolution of smart urban agriculture research. (a) Keyword co-occurrence network of the included literature; (b) temporal overlay visualization of keyword evolution from 2021 to 2025 (source: authors).

5. Applications of ICT Across Urban Agriculture Types

This section addresses RQ2 by examining how ICTs are applied across different types of urban agriculture. Based on the 143 studies included in the review, the literature was coded according to both ICT family and urban agriculture production scenario. Seven main scenarios were identified: vertical farming, plant factories with artificial lighting (PFALs), soilless cultivation, greenhouses and controlled-environment agriculture (CEA), rooftop

and building-integrated agriculture, urban and community gardens, and peri-urban open fields or vacant land. These categories are not entirely mutually exclusive. For example, plant factories often overlap with vertical farming and CEA, while hydroponic systems may appear in indoor farms, rooftop farms, or community-based settings. Nevertheless, they provide a useful analytical framework for comparing how ICT applications vary across different spatial and technical forms of urban agriculture.

As shown in Figure 4, ICT applications are unevenly distributed across these scenarios. They are concentrated in production systems with higher levels of technical controllability, especially soilless cultivation, vertical farming, plant factories, and other controlled-environment systems [29–31]. These settings provide stable, enclosed, and measurable growing environments, making them particularly suitable for sensor-based monitoring, automated control, machine learning prediction, and optimization. By contrast, more open, socially embedded, or spatially dispersed forms of urban agriculture, such as community gardens, rooftop gardens, vacant land cultivation, and peri-urban open fields, are less prominent in the ICT-oriented literature.

ICT \ Scenario	Plant Factory (PFAL)	Vertical Farming	Greenhouse / CEA	Soilless Cultivation (Hydro/Aero/Aquaponic)	Rooftop / Building-Integrated	Urban / Community Gardens	Peri-Urban Open Fields and Vacant Land
IoT, Sensors, and Wireless Networks	14	31	14	43	3	11	9
AI and Machine Learning	12	30	9	25	5	2	14
Computer Vision and Imaging	5	7	4	10	1	0	3
Automation and Control Systems	11	16	12	24	2	5	3
Robotics and Autonomous Systems	0	6	1	4	1	1	2
GIS, Remote Sensing, and Spatial Analysis	0	1	0	1	4	4	13
Digital Twins, DSS, and Data Platforms	8	15	5	14	4	8	8

Figure 4. ICT × Scenario matrix heatmap (source: authors). Cell values are publication counts, the number of reviewed studies coded for both the corresponding ICT category and scenario. Because both axes are multi-label, a single study may be coded under several ICT categories and/or several scenarios and is counted in each matching cell.

Across the reviewed studies, IoT and sensor networks constitute the most widely used technological foundation. They are particularly common in soilless cultivation and controlled-environment systems, where continuous monitoring of pH, electrical conductivity (EC), dissolved oxygen (DO), water temperature, air temperature, humidity, and nutrient concentration is essential for crop management [32–34]. AI and machine learning form the second major category of technologies, increasingly applied to disease recognition, yield prediction, growth modeling, energy optimization, and environmental parameter control [17,18,35]. Automation and control systems form the third major category, particularly in controlled-environment systems, whereas computer vision, robotics, digital twins, GIS, and remote sensing remain more selective in their application. Robotics is still largely exploratory, digital twins are emerging as integrative modeling and decision-support platforms, and GIS and remote sensing are used mainly for open-space, rooftop, and larger-scale spatial analysis [36–40].

The distribution shown in Figure 4 suggests that smart urban agriculture is not developing evenly across all forms of urban food production. Instead, current research is concentrated in systems that are enclosed, data-rich, and technically controllable. This reflects a broader technological tendency: ICTs are first adopted where environmental variables can be measured, standardized, and adjusted with relative precision. However, this concentration also reveals a limitation in the current literature. Forms of urban agriculture that are more socially embedded, spatially open, or governance-oriented remain less visible, even though they are central to wider debates on urban agriculture, food justice, land use,

and community resilience. The following subsections therefore examine ICT applications across different urban agriculture scenarios in order to clarify where smart technologies are most mature, where they remain experimental, and where important gaps persist.

5.1. Vertical Farming

Vertical farming is treated in this review as a spatial production form characterized by multi-layer cultivation, intensive use of vertical space, artificial lighting, and enclosed or semi-enclosed microclimatic control. Compared with conventional planar cultivation, these characteristics make vertical farming more dependent on environmental sensing, lighting control, energy management, and automated operation [31,41]. IoT and sensor networks are therefore widely applied in this scenario to monitor variables such as temperature, humidity, CO₂ concentration, light intensity, and airflow across different cultivation layers [42–44]. As the scale and complexity of vertical farming systems have increased, the literature has moved beyond simple threshold-based monitoring toward more stable and distributed management supported by wireless sensor networks, edge computing, and long-range communication architectures [45–47].

AI and machine learning have further extended the functions of ICT in vertical farming from monitoring to prediction and optimization. These technologies have been used to predict crop growth, yield, vapor pressure deficit (VPD), lighting requirements, and energy consumption [35,48–50]. This shift indicates that smart vertical farming is no longer limited to observing environmental conditions, but increasingly seeks to model how different combinations of light, temperature, humidity, and nutrient conditions affect crop performance and production efficiency. In particular, yield prediction and model predictive control (MPC) support a more integrated balance among crop growth, lighting strategy, cultivation cycle, and energy cost [51,52].

Energy optimization has become one of the most important directions of ICT application in vertical farming. Because artificial lighting and heating, ventilation, and air-conditioning (HVAC) systems constitute major operating costs, recent research increasingly incorporates energy consumption into production decisions [41,50]. AI, MPC, and cyber-physical systems (CPS) have been used to coordinate lighting duration, temperature set-points, cultivation schedules, and resource use [51,52]. This suggests that vertical farming research is moving from environmental control alone toward the coordinated optimization of biological growth, technical operation, and economic performance.

Computer vision and robotics have also begun to appear in vertical farming research, although their maturity remains lower than that of IoT-based monitoring and AI-based prediction. Computer vision is used mainly for plant segmentation, growth monitoring, phenotyping, and image-based crop assessment under high-density cultivation conditions [53,54]. Robotics is applied mainly to harvesting, inspection, and dynamic monitoring in multi-layer production systems [55,56]. Although the number of relevant studies remains limited, these applications point toward the gradual development of more autonomous vertical farming systems.

Overall, ICT applications in vertical farming follow a clear functional progression: from high-density environmental sensing, to AI-based prediction and energy optimization, and then toward automation and autonomous operation (Table 2). The most mature technologies are still IoT and sensor networks, which provide the basic data infrastructure for vertical farming. AI and ML provide the most visible improvement in terms of prediction and optimization, while robotics and computer vision represent emerging but less mature directions. This trajectory reflects the broader transformation of vertical farming from a controlled production space into an increasingly data-driven and cyber-physical production system.

Table 2. Representative studies of ICT applications in vertical farming (source: authors; only representative studies are listed).

Study ID	Application Task	ICT Family	Scenario
S021	Growth monitoring and RoI prediction	AI/machine learning; Computer vision	Vertical Farming; Soiless Cultivation
S053	Dynamic plant and fruit monitoring	IoT; AI/machine learning; Robotics	Vertical Farming; Soiless Cultivation
S090	Effect of LED lighting on growth	IoT	Vertical Farming; Soiless Cultivation
S094	Robotic in situ harvesting	Robotics	Vertical Farming; Soiless Cultivation
S130	Edge-based autonomous monitoring	IoT; Digital twins/DSS	Vertical Farming

Note: Study IDs refer to Supplementary Table S4. S021 Hwang et al. [53]; S053 Yang et al. [56]; S090 Kuankid et al. (2022); S094 Yu and Jiang [55]; S130 Jandl et al. [46].

5.2. Soiless Cultivation

Soiless cultivation is treated in this review as a cultivation system rather than a purely spatial form of urban agriculture. It includes hydroponics, aeroponics, and aquaponics, and often overlaps with vertical farming, plant factories, rooftop farming, and controlled-environment agriculture. Its defining feature is the replacement of soil with an artificially managed growing medium or nutrient solution. As a result, crop growth depends heavily on the monitoring and regulation of water quality, nutrient composition, and root-zone conditions [32,33,57]. This makes soiless cultivation one of the most data-intensive and technically controllable scenarios in smart urban agriculture, and explains why IoT and sensor networks have become particularly mature in this field.

Nutrient solution monitoring and control represents the most established ICT application in soiless cultivation. Sensors are widely used to measure parameters such as pH, electrical conductivity (EC), total dissolved solids (TDS), temperature, dissolved oxygen, and nutrient concentration. These data are then used to support nutrient regulation through microcontrollers, automated pumps, and fuzzy-logic control systems [27,32,33]. The technical logic has therefore shifted from simple environmental monitoring toward closed-loop control, in which sensing, diagnosis, and adjustment are connected within the same system. Recent studies have further introduced context-aware control, edge processing, and low-power long-range communication, improving the stability and adaptability of small-scale urban cultivation systems [34,58].

AI and machine learning have become increasingly relevant in more complex soiless systems, particularly aquaponics. Unlike ordinary hydroponics, aquaponics involves the interaction of fish, plants, microorganisms, water quality, and nutrient cycling. Its higher degree of system coupling creates greater uncertainty and makes real-time prediction and decision support more important. AI models have therefore been used to predict water quality changes, identify abnormal system states, and support management decisions [43,59]. Digital twins and decision-support systems have also begun to appear in this area, suggesting a shift from single-parameter monitoring toward system-level modeling and integrated management [15,36,60].

Computer vision further extends the intelligence of soiless cultivation by linking crop state observation with management decisions. Vision-based techniques have been used for crop health diagnosis, disease recognition, phenotyping, and adaptive fertilization [61,62]. The key development is that visual data are increasingly used not only to observe crop conditions, but also to guide operational responses such as fertilization and nutrient adjustment. In this sense, computer vision contributes to the formation of a sensing–diagnosis–decision–execution loop in soiless cultivation systems.

Soiless cultivation also has strong potential for low-cost dissemination. Many reviewed studies developed small-scale IoT systems using ESP32, Arduino, Raspberry Pi, smartphones, and open-source platforms [44,57]. These systems are not necessarily the

most technically advanced, but they are important because they lower the threshold for urban residents, small farms, schools, and community spaces to adopt smart-agriculture technologies. In addition, AI has been used for yield prediction and growth optimization in hydroponic and aeroponic systems [49,63,64].

Overall, soilless cultivation is among the most technically mature and replicable areas of smart urban agriculture (Table 3). Its maturity derives from the high controllability of water, nutrients, and root-zone conditions, which makes it particularly suitable for sensor-based monitoring, closed-loop control, AI-assisted prediction, and decision support. The reviewed studies suggest a clear technological progression from nutrient solution monitoring, to automated regulation, and increasingly toward system-level optimization and low-cost adoption. Compared with vertical farming, which is strongly shaped by spatial stacking and energy-management challenges, soilless cultivation is defined more by its controllable cultivation medium and its capacity to support modular, scalable, and relatively accessible smart-agriculture systems.

Table 3. Representative studies of ICT applications in soilless cultivation (source: authors; only representative studies are listed).

Study ID	Application Task	ICT Family	Scenario
S055	Nutrient solution pH/TDS monitoring and classification	IoT; AI/machine learning; Automation and control	Soilless Cultivation
S113	Closed-loop nutrient solution regulation	IoT; Automation and control	Soilless Cultivation
S028	High-altitude pH/EC regulation	IoT; Automation and control	Soilless Cultivation
S050	Adaptive root-zone temperature management	IoT; Automation and control	Soilless Cultivation
S042	Water quality prediction	AI/machine learning	Soilless Cultivation
S107	System-level decision support	AI/machine learning; Digital twins/DSS	Vertical Farming; Soilless Cultivation
S112	Vision-phenotyping-driven fertilization	AI/machine learning; Computer vision; Automation and control	Plant Factory; Soilless Cultivation
S092	Disease diagnosis	AI/machine learning; Computer vision	Soilless Cultivation
S068	Yield prediction	IoT; AI/machine learning	Vertical Farming; Soilless Cultivation
S063	Growth optimization	IoT; AI/machine learning	Soilless Cultivation

Note: Study IDs refer to Supplementary Table S4. S055 Herman et al. [32]; S113 Agustian et al. [33]; S028 Escalante-Mamani et al. [34]; S050 Trang et al. [58]; S042 Majid & Setiawan [59]; S107 Ghandar et al. [36]; S112 Concepcion et al. [61]; S092 Kulkarni & Gohokar [62]; S068 Rajendiran & Rethnaraj [49]; S063 Kumaraguru-rubaran et al. [64].

5.3. Greenhouse and Controlled-Environment Agriculture

Greenhouses and controlled-environment agriculture (CEA) represent an intermediate scenario between open-field urban agriculture and fully enclosed systems such as plant factories. In this review, this category includes greenhouse-based production and other protected cultivation systems where environmental variables can be partly or fully regulated. ICT applications in this scenario are concentrated mainly in microclimate prediction, crop state monitoring, and operational automation [29,30].

The most evident contribution of ICT to greenhouse and CEA systems is the shift from reactive environmental control to predictive control. Conventional greenhouse automation typically adjusts environmental conditions after variables such as temperature, humidity, or light intensity exceed predefined thresholds. Recent studies, however, increasingly use machine learning, edge computing, high-density sensor networks, and field-programmable gate array (FPGA) systems to anticipate microclimate changes and adjust environmental

conditions in advance [65]. Predictive control can reduce the response lag of greenhouse systems and improve the precision of environmental regulation, particularly where temperature, humidity, ventilation, and irrigation need to be coordinated.

Computer vision is another active area of ICT application in greenhouses and CEA. Image-based methods using RGB images, RGB-D images, and thermal imaging have been used to estimate leaf area, plant height, fresh weight, stress symptoms, and crop health [66,67]. These techniques allow crop-growth states to be quantified more continuously and non-destructively, thereby supporting more refined management decisions. Compared with conventional manual observation, computer vision improves the capacity of greenhouse systems to detect growth variation, identify stress, and adjust management practices in a more timely manner.

Automation and robotics also have application potential in greenhouse scenarios, particularly for repetitive operations and labor-intensive tasks [68]. Compared with open-field or community-based spaces, greenhouses provide a more structured environment and are therefore more suitable for robotic operation. However, robotics is not yet a mainstream technology in this scenario. Most applications remain experimental or task-specific, focusing on inspection, movement assistance, or selected cultivation operations rather than full-process automation.

Greenhouses and CEA are also important carriers for the smart cultivation of specialty food products, including edible fungi. Studies on oyster mushroom production, for example, have used IoT sensors and fuzzy-control systems to regulate temperature and humidity in response to crop-specific growth requirements [69,70]. These studies show that ICT is not limited to leafy vegetables or hydroponic crops, but can also support the controlled cultivation of food products with highly specific environmental needs.

Overall, the main value of ICT in greenhouses and CEA lies in improving environmental prediction, crop state recognition, and localized operational automation (Table 4). This scenario occupies a transitional position in smart urban agriculture. It is more technically controllable than open-field or community-based agriculture, but generally less standardized and system-integrated than plant factories. Greenhouses and CEA therefore represent an important pathway through which conventional protected agriculture is being upgraded toward more intelligent, data-driven production systems.

Table 4. Representative studies of ICT applications in greenhouse/CEA (source: authors; only representative studies are listed).

Study ID	Application Task	ICT Family	Scenario
S022	Review of deep learning applications in CEA	AI/machine learning	Plant Factory; Vertical Farming; Greenhouse/CEA
S047	Edge-intelligence microclimate prediction	IoT; AI/machine learning; Automation and control	Greenhouse/CEA
S110	Crop morphological-parameter prediction	AI/machine learning; Computer vision	Greenhouse/CEA
S044	Stress symptom grading	IoT; AI/machine learning; Computer vision	Plant Factory
S127	Operational automation	Robotics	Greenhouse/CEA; Community Gardens
S024	Specialty-crop environmental control	IoT; Automation and control	Greenhouse/CEA; Community Gardens
S039	Edible-fungi climate control	IoT; Automation and control	Greenhouse/CEA; Community Gardens

Note: Study IDs refer to Supplementary Table S4. S022 Ojo & Zahid [30]; S047 Dafhalla et al. [65]; S110 Kang et al. [66]; S044 Lee et al. [67]; S127 García-Venegas et al. [68]; S024 Foffano et al. [69]; S039 Ariffin et al. [70].

5.4. Plant Factory

Plant factories with artificial lighting (PFALs), to some extent, overlap with vertical farming and controlled-environment agriculture, but they represent the most enclosed, standardized, and industrialized end of the smart urban agriculture spectrum. In this review, the PFAL is treated as a distinct scenario because its ICT applications emphasize multi-system integration rather than the use of a single technology. IoT sensing, AI prediction, automated control, cyber-physical systems, and decision-support architectures are often combined to regulate production in a highly controlled indoor environment [29,71,72].

In plant factories, sensors continuously collect environmental, physiological, and operational data, while automation systems regulate lighting, temperature, humidity, CO₂ concentration, irrigation, and nutrient supply [72,73]. AI and machine learning are used to predict crop responses, optimize growth conditions, and improve production efficiency [74]. In this sense, PFALs function as representative testbeds for highly integrated smart agriculture systems, where biological growth processes, engineering control systems, and data-driven decision-making are closely connected.

Energy consumption is one of the most important challenges faced by plant factories. Because PFAL systems depend heavily on artificial lighting and heating, ventilation, and air-conditioning systems, ICT is not used only to maintain an optimal crop-growth environment; it is also used to coordinate crop growth, energy consumption, and production cost. AI, model predictive control (MPC), and cyber-physical-biological systems (CPBSs) can integrate biological processes, engineering controls, and economic objectives within a single decision-making framework [51]. This is one of the areas in which AI offers particularly visible improvements, because it enables plant factories to move from environmental stability toward energy–production co-optimization.

High-throughput phenotyping is another important ICT application in plant factories. Image recognition, fluorescence imaging, hyperspectral data, and online biomass estimation have been used for non-destructive monitoring of crop traits [50,72,75]. These techniques allow crop growth, biomass accumulation, and physiological responses to be measured more precisely and reproducibly. They also support more standardized experimentation and management, which is especially important in fully enclosed production systems where small environmental adjustments can have measurable effects on crop performance.

Overall, plant factories represent the highest degree of system integration among the smart urban agriculture scenarios reviewed in this study (Table 5). Their ICT applications are not limited to monitoring or control, but extend to the integration of sensing, modeling, prediction, automation, and optimization. However, their wider dissemination remains constrained by high energy consumption, high capital cost, and substantial technical requirements. PFALs therefore illustrate both the technological frontier and the practical limits of smart urban agriculture: they show how far data-driven agricultural control can be developed, but also how dependent such systems are on infrastructure, energy, finance, and technical expertise.

Table 5. Representative studies of ICT applications in plant factories (source: authors; only representative studies are listed).

Study ID	Application Task	ICT Family	Scenario
S075	Industrial communication and computing architecture	IoT; Digital twins/DSS	Plant Factory; Vertical Farming
S062	Integrated intelligent environmental control	IoT; AI/machine learning; Automation & control	Plant Factory; Vertical Farming
S079	Real-time nitrogen regulation	IoT; AI/machine learning; Automation & control	Plant Factory

Table 5. *Cont.*

Study ID	Application Task	ICT Family	Scenario
S054	Growth and quality prediction	IoT; AI/machine learning	Plant Factory; Soilless Cultivation Vertical Farming
S077	Non-destructive biomass monitoring	IoT	
S105	Energy–production coordination	AI/machine learning; Automation and control; Digital twins/DSS	Plant Factory

Note: Study IDs refer to Supplementary Table S4. S075 Liu et al. [71]; S062 Kaya [72]; S079 Sun et al. [73]; S054 Kim et al. [74]; S077 Munser et al. [75]; S105 Hu & You [51].

5.5. Rooftop, Building-Integrated, and Community-Garden Agriculture

Rooftop and building-integrated agriculture on the one hand, and urban and community gardens on the other, represent two distinct production scenarios. However, they are discussed together in this section because their ICT applications share several characteristics. Compared with soilless cultivation, vertical farming, and plant factories, these forms of urban agriculture are often smaller in scale, spatially dispersed, more exposed to urban environmental conditions, and managed by multiple actors. Their objectives also frequently extend beyond yield maximization to include building energy performance, urban greening, stormwater management, education, social interaction, community building, and food equity [29,76–78]. As a result, high-intensity ICT applications such as full-process automation, AI-driven optimization, and robotics are less prominent in these scenarios.

In rooftop and building-integrated agriculture, ICT is used mainly to support the integration of food production with buildings and urban space. The research focus therefore shifts from the regulation of enclosed growing environments to the assessment of building environment constraints and the coupling between cultivation, architecture, and resource flows. Existing studies apply ICTs to environmental monitoring, irrigation control, rooftop microclimate analysis, solar radiation mapping, building energy assessment, and productive façade optimization [76,79,80]. Sensors can be used to monitor temperature, humidity, substrate moisture, and crop growing conditions, while GIS, spatial analysis, and digital-twin tools can support rooftop inventory, site suitability assessment, and design evaluation [37,77]. Compared with enclosed production systems, AI and automation are less frequently applied. The main value of ICT in this scenario is therefore not to enable full automation, but to support spatial identification, environmental monitoring, building performance assessment, and resource management.

Urban and community gardens show an even stronger social and organizational dimension. These spaces are often managed by residents, schools, community organizations, non-profit institutions, or local partnerships. Accordingly, ICT applications are generally less production-intensive and more oriented toward coordination, monitoring, and participation. Existing studies use sensors, mobile applications, GIS, remote sensing, UAV imagery, and digital platforms to support resource management, spatial identification, irrigation monitoring, and community-based cultivation [81–83]. GIS and remote sensing can help identify suitable land for community agriculture and map garden land use and vegetation diversity [38]. Sensors can support soil moisture monitoring and irrigation decisions, while digital platforms and mobile applications can help coordinate participants, record cultivation activities, and disseminate agricultural knowledge [78]. In this scenario, ICT contributes less to yield maximization than to lowering participation barriers, improving organizational efficiency, and supporting social and educational objectives.

Taken together, these two scenarios show that smart urban agriculture should not be understood only as a technology-intensive production system (Tables 6 and 7). If intelligence is measured solely by the degree of automation, AI application, or environmental

controllability, the value of socially embedded and spatially integrated forms of urban agriculture may be underestimated. Rooftop and building-integrated agriculture require ICT tools that can connect building performance, food production, microclimate, water use, and urban ecological benefits. Community gardens require ICT tools that can support participation, knowledge sharing, resource coordination, food equity, and public space governance. This suggests that smart urban agriculture contains not only a production optimization pathway, represented by vertical farming, PFALs, and soilless cultivation, but also an enabling pathway, in which ICT supports the spatial, social, and governance functions of urban agriculture.

Table 6. Representative studies of ICT applications in rooftop and building-integrated agriculture (source: authors; only representative studies are listed).

Study ID	Application Task	ICT Family	Scenario
S051	Solar radiation mapping and design support	GIS/remote sensing; Digital twins/DSS	Rooftop/BIA; Peri-Urban
S036	Productive façade performance prediction	AI/machine learning	Vertical Farming; Rooftop/BIA
S119	Building energy–food self-sufficiency optimization	AI/machine learning	Vertical Farming; Rooftop/BIA
S070	Smart green façade and water saving	IoT; Automation and control	Rooftop/BIA
S116	Rooftop space inventory	GIS/remote sensing	Rooftop/BIA

Note: Study IDs refer to Supplementary Table S4. S051 Clementi et al. [37]; S036 Hao et al. [76]; S119 Ekici et al. [80]; S070 Lassandro et al. [79]; S116 Wang & Zhang [77].

Table 7. Representative studies of ICT applications in community gardens (source: authors; only representative studies are listed).

Study ID	Application Task	ICT Family	Scenario
S027	Outdoor household smart cultivation	IoT; Automation and control; Digital twins/DSS	Community Gardens
S045	Personal smart agriculture in apartments	IoT	Community Gardens
S057	Mobile monitoring for container gardening	IoT; Digital twins/DSS	Community Gardens
S124	Garden land use and diversity mapping	AI/machine learning; GIS/remote sensing	Community Gardens
S093	Technology adoption in household gardening	IoT; Digital twins/DSS	Soilless Cultivation; Community Gardens

Note: Study IDs refer to Supplementary Table S4. S027 Maslan et al. [81]; S045 Shuhaimi et al. [82]; S057 Madhusanka et al. [83]; S124 Wagner & Egerer [38]; S093 Ibarra-Cabrera et al. [78].

5.6. Peri-Urban Open Fields and Vacant Land

Peri-urban open fields and vacant land represent a distinctive ICT application scenario within smart urban agriculture. Unlike vertical farming, plant factories, and soilless cultivation, these spaces are open, spatially extensive, and strongly shaped by land use change, infrastructure conditions, environmental constraints, and planning regulations. Their ICT applications are therefore less concerned with high-density sensing or automated environmental control within a single facility. Instead, they rely mainly on GIS, remote sensing, spatial modeling, land suitability assessment, and multi-criteria decision analysis to evaluate agricultural potential at the urban fringe or within underused urban land [39,40,84].

In this scenario, ICT is used primarily to identify the agricultural potential of peri-urban or vacant land, monitor land use change, assess the feasibility of converting

underused spaces into productive landscapes, and analyze the impact of urban expansion on agricultural land. Remote sensing and machine learning are commonly used to monitor cropland change, classify crop types, and estimate yield under urban expansion pressures [43,84,85]. GIS-based approaches, meanwhile, support site selection, land suitability analysis, environmental impact assessment, and food equity mapping [40,86]. These applications provide cross-scale spatial information that cannot be generated through facility-level sensors alone.

Compared with controlled-environment agriculture, AI and IoT are less prominent in peri-urban open fields and vacant land studies. This does not indicate that these spaces are less important within smart urban agriculture. Rather, it reflects a different set of technical requirements. Open and peri-urban spaces are shaped by land availability, location, soil quality, water access, infrastructure, contamination risk, market proximity, and policy conditions, rather than by microclimate control inside a closed system [87–89]. Accordingly, ICT in this scenario functions more as a tool for spatial diagnosis, environmental assessment, and planning support than as a tool for direct production control.

This distinction is important for understanding the wider scope of smart urban agriculture. If smartness is defined narrowly as real-time sensing, automation, and AI-based crop management, peri-urban open fields and vacant land may appear technologically marginal. However, if smart urban agriculture is understood more broadly as the use of digital tools to support food production within complex urban systems, then GIS, remote sensing, spatial modeling, and land suitability assessment become central. They connect agricultural production with urban expansion, land governance, environmental risk, and food access planning.

Overall, peri-urban open fields and vacant land represent a spatial governance pathway of smart urban agriculture (Table 8). Their technological logic differs from the production optimization pathway found in vertical farming, soilless cultivation, and plant factories. Rather than optimizing the internal conditions of a controlled production unit, ICT is used here to identify where urban agriculture can occur, how land use change affects agricultural capacity, and how vacant or fringe spaces can be incorporated into more resilient urban food systems.

Table 8. Representative studies of ICT applications in peri-urban open fields and vacant land (source: authors; only representative studies are listed).

Study ID	Application Task	ICT Family	Scenario
S097	Cropland change monitoring	AI/machine learning; GIS/remote sensing	Peri-Urban
S115	Yield estimation under urban expansion	AI/machine learning; GIS/remote sensing	Peri-Urban
S098	Crop-type mapping	AI/machine learning; GIS/remote sensing	Peri-Urban
S041	Site selection and food equity mapping	GIS/remote sensing; Digital twins/DSS	Peri-Urban
S118	Environmental impact of peri-urban agriculture	GIS/remote sensing; Digital twins/DSS	Peri-Urban
S131	Soil heavy-metal pollution assessment	GIS/remote sensing	Peri-Urban
S129	Local meteorological-feature extraction	AI/machine learning	Rooftop/BIA; Community Gardens
S104	Robotic intervention against field bird damage	Robotics	Peri-Urban

Note: Study IDs refer to Supplementary Table S4. S097 Nasser & Adam [39]; S115 Mandigo et al. [84]; S098 Sun et al. [85]; S041 Kamali et al. [40]; S118 Mendoza Beltran et al. [86]; S131 Wang et al. [88]; S129 Huang & Chang [89]; S104 Brown & Brown (2021).

5.7. Summary

Overall, ICT applications in urban agriculture show clear differentiation across production scenarios. Soilless cultivation, vertical farming, and plant factories are currently the most technology intensive areas of smart urban agriculture. In these scenarios, IoT, AI, automated control, and computer vision increasingly form a relatively complete sensing–prediction–control–optimization chain [29–31]. Greenhouses and controlled-environment agriculture occupy a transitional position, where ICT is used mainly to upgrade conventional protected cultivation through predictive microclimate control, crop state recognition, and localized automation [65,66].

By contrast, rooftop and building-integrated agriculture, community gardens, and peri-urban open fields are less frequently represented in technology-intensive ICT research. This does not mean that their importance within smart urban agriculture is lower. Rather, their technological logic is different. In these scenarios, ICT is used less for full-process automation or yield maximization, and more for spatial identification, environmental monitoring, resource management, community participation, food equity assessment, and urban governance [40,77,78]. They therefore represent an enabling and spatial governance pathway of smart urban agriculture, in contrast to the production optimization pathway represented by vertical farming, soilless cultivation, and plant factories.

The current literature thus reveals two parallel tendencies. At the technical level, smart urban agriculture is moving from sensing-based monitoring toward AI-assisted prediction, decision support, automated control, and system optimization [14,17]. At the level of the research landscape, however, the field is selectively concentrated in enclosed, standardized, and technically controllable production systems. These systems are more suitable for experimentation, data collection, and performance evaluation, but they do not represent the full range of urban agriculture. More socially embedded, spatially open, and governance-oriented forms remain comparatively underexplored.

At the present stage, IoT and sensor networks remain the most mature and widely used technological foundation because they provide the data infrastructure for almost all intelligent applications. AI and machine learning offer the most visible improvement by transforming environmental and crop data into prediction, optimization, and decision support. Digital twins, decision-support systems, robotics, and cross-scale spatial analysis tools are emerging directions, but their applications remain uneven across different UA scenarios [36,37]. The central challenge for future research is therefore not only to improve the technical sophistication of smart urban agriculture, but also to broaden its application beyond highly controllable production systems toward more diverse urban, community-based, and governance-oriented contexts.

6. Discussion: Current Status, Barriers, and Future Directions

This section addresses RQ3 by discussing the current status of smart urban agriculture, the barriers that constrain its wider adoption, and future research directions. Building on the bibliometric and thematic analysis in Section 4 and the scenario-based synthesis in Section 6, the discussion shows that smart urban agriculture has developed into an emerging research field with a recognizable technological structure, but that its development remains uneven across production scenarios, regions, and analytical scales.

6.1. From Scattered Experiments to an Emerging Research Field

The review shows that smart urban agriculture has moved from a marginal topic at the intersection of urban agriculture and smart farming toward a more visible and rapidly expanding research area. The publication trajectory from 2016 to 2026 indicates that the field entered a phase of rapid growth after 2021. This suggests that ICT-enabled urban agriculture

is no longer limited to scattered technical experiments, but is increasingly forming a body of literature organized around IoT, sensor networks, machine learning, soilless cultivation, vertical farming, plant factories, and controlled-environment agriculture.

This finding addresses a gap in earlier reviews, which tended to examine smart agriculture and urban agriculture separately rather than at their intersection [21,22,26]. The contribution of this review lies in treating urban agriculture forms and ICT families as two interconnected analytical dimensions. This approach shows that smart urban agriculture is not a simple process of transferring rural precision-agriculture technologies into cities. Rather, it is shaped by the interaction between urban spatial constraints, production-system characteristics, and digital technological capabilities.

From a technological perspective, the field displays a progressive pathway from environmental monitoring, to system connectivity, and then toward intelligent prediction and automated control. Early studies relied mainly on sensors, wireless networks, and remote monitoring systems to collect environmental parameters such as temperature, humidity, pH, electrical conductivity, dissolved oxygen, and light intensity. The Internet of Things then became the key infrastructure connecting crops, equipment, environments, and managers. More recently, machine learning, deep learning, and computer vision have supported predictive management, including yield estimation, disease recognition, crop state assessment, energy optimization, and closed-loop control [14,16–18].

This trajectory indicates that ICT is shifting from an auxiliary monitoring tool to a production-decision infrastructure. However, the current literature remains largely technology- and production-oriented. Many studies focus on crop growth, environmental regulation, and operational efficiency within a single facility or production system. By contrast, the urban dimension is often treated mainly as the spatial background of production, rather than as a core analytical scale for examining food systems, land use, spatial governance, community participation, or sustainable urban development.

6.2. Uneven Technological Development Across Urban Agriculture Scenarios

The review also reveals strong differentiation across urban agriculture scenarios. Soilless cultivation, vertical farming, plant factories, and greenhouses/CEA are the most technology-intensive fields because they depend heavily on artificial regulation and require continuous monitoring of water, nutrients, light, temperature, humidity, ventilation, and crop status. In these scenarios, IoT and sensors provide the data foundation, AI and machine learning support prediction and optimization, and automation and robotics are gradually being introduced into environmental regulation, harvesting, handling, and inspection.

By contrast, rooftop agriculture, community gardens, peri-urban open fields, and vacant land show a different technological logic. ICT applications in these scenarios are less focused on full-process automation or high-precision production control. Instead, they are more commonly associated with GIS-based site selection, remote sensing monitoring, UAV mapping, simple environmental sensing, mobile management, public participation, and spatial planning support. This difference suggests that the degree of digitalization in smart urban agriculture depends strongly on the controllability of the production system. The more enclosed, standardized, and industrialized a production system is, the easier it is for ICT to form a complete “sensing–prediction–control–optimization” chain. The more open, community-based, or socially embedded a scenario is, the more its ICT application is shaped by land tenure, maintenance capacity, user skills, institutional support, and social acceptance.

This finding points to a central limitation in the current research landscape: smart urban agriculture is strong in production technology but weak in urban integration. Keyword co-occurrence results show that urban agriculture, IOTs, and hydroponics form the core of

the existing knowledge network, while terms related to governance, planning, community participation, food equity, policy, and institutions are much less visible. This indicates that existing research tends to understand urban agriculture as a production system that can be monitored, optimized, and automated, rather than as part of wider urban food systems and governance arrangements.

This production-oriented bias has generated important technical advances, but it also narrows the potential contribution of smart urban agriculture to urban sustainability. The value of urban agriculture cannot be assessed only through yield, efficiency, or environmental control. It also relates to food accessibility, ecosystem services, community resilience, education, public space use, and shorter and more transparent urban food supply chains [10,25]. Future research therefore needs to examine not only whether ICT improves production performance, but also whether it strengthens the wider urban functions of urban agriculture.

6.3. Geographical Imbalance and Limits of Generalizability

The geographical distribution of the reviewed literature further limits the generalizability of existing findings. The United States, China, and South Korea account for a relatively large proportion of the corpus, while many regions of Africa, Central Asia, Eastern Europe, and Latin America remain underrepresented. This does not mean that these regions lack demand for smart urban agriculture. On the contrary, many low- and middle-income cities face acute pressures related to food security, water scarcity, land competition, urban expansion, and climate adaptation.

The current evidence base therefore reflects not only where smart urban agriculture is being practiced or needed, but also where research funding, technical infrastructure, data availability, and academic publishing capacity are concentrated. As a result, many ICT solutions are developed and tested in contexts with relatively strong technological capacity, controlled-environment infrastructure, and institutional support. Their effectiveness in resource-constrained cities, informal settlements, community-managed gardens, and rapidly urbanizing regions remains insufficiently examined.

This geographical imbalance has both empirical and methodological implications. Empirically, it limits understanding of how smart urban agriculture works under conditions of high informality, limited maintenance capacity, unstable land tenure, weak infrastructure, or constrained public funding. Methodologically, it means that models and systems validated in one context may not be easily transferred to another. Future research should therefore place greater emphasis on low-cost, low-maintenance, and context-sensitive ICT applications in cities of the Global South and other underrepresented regions.

6.4. Methodological Barriers: Data, Evaluation, and System Integration

At the methodological level, the reviewed literature faces three major barriers: data limitations, narrow evaluation criteria, and insufficient system integration.

First, many technical studies rely on a single case, a single crop, or a small-scale experimental setting. While such studies are useful for demonstrating feasibility, they often lack validation across different cities, climate zones, crop types, and production systems. This limits the transferability of models and makes it difficult to assess whether reported performance can be sustained under more diverse urban conditions.

Second, evaluation indicators remain heavily oriented toward technical performance. Many studies emphasize prediction accuracy, recognition accuracy, sensing stability, response speed, or control precision. These indicators are important, but they do not fully capture the objectives of urban agriculture. Broader indicators, including energy cost, carbon emissions, water use efficiency, labor accessibility, maintenance requirements, food

accessibility, community acceptance, and policy compatibility, are less frequently incorporated. As a result, it remains difficult to evaluate whether smart urban agriculture is successful as an urban sustainability strategy, rather than only as a technical production system.

Third, ICT applications often appear as isolated modules. Sensors, AI models, control systems, GIS tools, and digital platforms are frequently developed and evaluated separately. However, smart urban agriculture requires stronger interoperability between sensing, data management, prediction, control, spatial assessment, and governance decision-making. This echoes wider discussions in smart agriculture on data value chains, platform governance, and business models [14,26]. The next stage of development therefore requires a shift from single-point technological applications toward integrated decision-support systems.

6.5. Future Research Directions

Future research should advance in three directions. First, multi-source data integration should be strengthened. Smart urban agriculture requires the integration of sensor data, remote sensing imagery, crop phenotypes, energy consumption, climate data, land use information, infrastructure data, and socioeconomic indicators. Such integration would support cross-scale decision-making, connecting micro-level crop management with building performance, neighborhood planning, urban food system analysis, and spatial governance.

Second, more attention should be paid to edge computing, digital twins, decision-support systems, and closed-loop control. These technologies can help smart urban agriculture move beyond monitoring toward simulation, prediction, optimization, and adaptive management. Edge computing is particularly important for reducing latency and improving system reliability in small-scale or resource-constrained settings. Digital twins and decision-support systems can connect environmental sensing, crop modeling, energy use, spatial assessment, and management decisions within a more integrated analytical framework.

Third, future research should incorporate social equity, user adoption, policy conditions, and commercial feasibility into the evaluation of smart urban agriculture. Intelligence should not be equated with technological complexity. In community gardens, household cultivation, school gardens, and resource-constrained cities, low-cost, maintainable, understandable, and participatory ICT solutions may have greater practical value than highly automated systems. Evaluating smart urban agriculture therefore requires attention to affordability, usability, governance arrangements, institutional support, and the distribution of benefits among different urban groups.

Overall, the scientific value of smart urban agriculture lies in its potential to connect digital technology, urban spatial resources, and sustainable food system governance. This review shows that the field has already developed a relatively mature technical foundation in controlled-environment production, soilless cultivation, and intelligent monitoring. However, clear gaps remain in open urban spaces, social participation, policy embedding, cross-regional validation, and integrated urban-scale decision support. The next stage of smart urban agriculture should therefore not pursue only higher-precision sensors, more complex algorithms, or more automated equipment. It should also develop integrated and context-sensitive systems that can support production efficiency, resource saving, food equity, community resilience, and urban governance at the same time.

7. Conclusions

This study set out to clarify the conceptual boundaries and consolidate the fragmented evidence base of smart urban agriculture, understood as the integration of ICTs into agricultural activities conducted within and around built-up urban areas. Although the digitalization of agriculture and the resurgence of urban food production have each

attracted substantial scholarly attention, prior reviews have tended to examine these two trajectories separately rather than at their intersection. As a result, the maturity, knowledge structure, technological applications, and limitations of smart urban agriculture have remained insufficiently assessed. Following the PRISMA 2020 guidelines, this paper conducted a systematic review and bibliometric analysis of 143 studies indexed in Web of Science and Scopus between 2016 and 2026. The review was organized around three questions concerning the conceptual foundations and publication trends of the field, the application of ICTs across different urban agriculture types, and the principal barriers and research gaps that remain.

The review yields three main findings. First, smart urban agriculture has developed rapidly since 2021 and is emerging as a recognizable research field organized around IoT, sensor networks, machine learning, soilless cultivation, vertical farming, plant factories, and controlled-environment agriculture. However, this development is geographically uneven. The United States, China, and South Korea account for a large share of the reviewed literature, while many low- and middle-income regions facing acute pressures related to food security, climate adaptation, land competition, and water scarcity remain underrepresented. This imbalance reflects differences in research capacity, technical infrastructure, and publication visibility, rather than differences in actual need.

Second, ICT applications differ substantially across urban agriculture types. Enclosed and technically controllable systems, such as soilless cultivation, vertical farming, plant factories, and greenhouses, have developed relatively mature sensing–prediction–control–optimization chains. In these contexts, IoT and sensor networks provide the data foundation, AI and machine learning support prediction and optimization, and automation and computer vision increasingly contribute to operational control and crop state recognition. By contrast, rooftop agriculture, building-integrated agriculture, community gardens, peri-urban open fields, and vacant land rely more on lighter and more spatially oriented tools, including GIS, remote sensing, UAV mapping, mobile applications, and basic environmental sensors. Their ICT applications are shaped less by full-process production control than by land availability, user capacity, maintenance costs, social acceptance, and governance conditions.

Third, the review reveals a core limitation in the current literature: smart urban agriculture is strong in production technology but comparatively weak in urban integration. Existing studies tend to understand urban agriculture as a production system that can be monitored, optimized, and automated, while paying less attention to its role within urban food systems, land use governance, public policy, community participation, and food equity. This imbalance is reinforced by methodological limitations, including limited cross-context validation, evaluation indicators focused primarily on technical performance, and insufficient interoperability among ICT modules.

The main contribution of this paper is to treat urban agriculture forms and ICT families as interconnected analytical dimensions. Rather than examining a single technology, crop, or production system, this review maps how technologies, spatial forms, and functional objectives are combined across a wider range of urban agriculture practices. In doing so, it reframes smart urban agriculture not as the simple transfer of rural precision-agriculture tools into cities, but as a distinct socio-technical field shaped by urban spatial constraints, production-system characteristics, and digital technological capabilities.

Several limitations should also be acknowledged. This review is restricted to English-language publications indexed in only two databases (Scopus and Web of Science), which may introduce a degree of geographical and disciplinary bias and understate research from non-anglophone regions. It did not include a formal quality or risk-of-bias assessment

of the included studies, and therefore characterizes how ICTs are applied rather than evaluating the rigor or performance of individual systems.

The findings also point to a future research agenda. First, stronger multi-source data integration is needed to connect sensor data, remote sensing imagery, crop phenotypes, energy consumption, land use information, and socioeconomic indicators across scales. Second, low-cost, interpretable, and maintainable ICT systems should receive greater attention, especially in community-based, resource-constrained, and multi-actor urban settings. Third, more empirical research is needed in cities of the Global South and other underrepresented regions. Fourth, future evaluation frameworks should incorporate not only technical accuracy and production efficiency, but also social equity, policy conditions, institutional feasibility, user adoption, commercial viability, and environmental performance.

Ultimately, the value of smart urban agriculture will depend not only on higher-precision sensors, more complex algorithms, or more automated equipment. It will depend on whether ICTs can support production efficiency, resource conservation, food accessibility, community resilience, and urban governance at the same time. Smart urban agriculture should therefore be understood not merely as a technological upgrade of urban food production, but as a potential pathway toward more integrated, inclusive, and sustainable urban food systems.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/agriculture16151668/s1>, Table S1: PRISMA checklist; Table S2: full list of the 143 reviewed articles; Table S3: coding manual with operational definitions and decision rules for the ICT and scenario axes; Table S4: full study-level coding on both axes and the 7×7 ICT $\times$ scenario co-occurrence matrix.

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Data Availability Statement: The full list of the 143 reviewed publications is provided as Supplementary Table S1. The operational definitions and decision rules used for coding are provided as Supplementary Table S2. The full study-level coding on both axes (ICT and scenario) and the 7×7 co-occurrence matrix underlying the heat map are provided as Supplementary Table S3. All analyzed records are drawn from publicly available academic publications indexed in Scopus and Web of Science; the search strategy and screening procedure are described in full in Section 3. No new experimental data were generated in this study.

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