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SURVEY PAPER

Vision-Based Autonomous UAV Landing: A Comprehensive Review of Technologies, Techniques, and Applications

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Abstract

Autonomous landing capabilities are critical for unmanned aerial vehicles (UAVs) operating in challenging environments, yet remain among UAV operations' most technically demanding aspects. This paper presents a comprehensive review of vision-based autonomous landing systems for UAVs, emphasising fiducial marker-based approaches. After systematically examining 143 papers published between 2018 and 2025, we critically analyse the evolution from traditional landing methods to advanced vision-based systems and evaluate their performance across diverse operational conditions. The review provides detailed analyses of marker design considerations, detection algorithms, performance metrics, and the impact of environmental factors like illumination, weather, and terrain on landing accuracy. We explore hardware implementation challenges, comparing FPGA, SoC, and GPU-based solutions for real-time vision processing on resource-constrained platforms. The integration of artificial intelligence accelerators and multi-sensor fusion approaches is examined, with quantitative comparisons of landing accuracy improvements across different methodologies. Contemporary trends, including swarm-based collaborative landing systems, self-reconfiguring markers, and machine learning-based adaptation to different environments, are discussed alongside regulatory frameworks and safety considerations. Real-world industrial implementations and technology transfer challenges are analysed to bridge the gap between academic research and commercial applications. This systematic review targets researchers, engineers, and stakeholders developing autonomous UAV landing systems for diverse applications, including emergency response, logistics, inspection, and environmental monitoring.

Keywords UAV · Autonomous landing · Vision-based navigation · Fiducial markers · Computer vision · Multi-sensor fusion · Edge computing · Deep learning · Marker detection · Embedded AI

1 Introduction

Unmanned aerial vehicles (UAVs) have transformed from niche technologies to integral components of various industries, revolutionising operations across domains including agriculture, delivery services, infrastructure inspection, disaster management, and security surveillance. Despite significant advancements in UAV capabilities, autonomous landing remains one of the most challenging operation phases, particularly in GPS-denied or visually complex environments.

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Traditional landing methods relying on manual control, GPS navigation, or radio beacons often struggle in these scenarios due to signal interference, human error, or lack of precision. These limitations have prompted intensive research into vision-based autonomous landing systems.

The critical importance of reliable landing systems cannot be overstated. As Kendall and Clarke [1] note, the risks associated with UAV operations – particularly during the approach and landing phases – are significant and must be actively mitigated through advanced control and sensing technologies. According to accident analyses, approximately 70% of UAV incidents occur during the landing phase, highlighting the need for robust autonomous landing capabilities. The economic implications are equally compelling, with Rifan et al. [2] reporting that delivery UAVs with autonomous precision landing systems achieve 87% higher operational efficiency and 63% reduced maintenance costs.

Vision-based landing systems leverage optical sensors and computer vision algorithms to detect, track, and land on designated targets without relying on external positioning technologies. Among these approaches, fiducial marker-based systems have gained significant traction due to their reliability, computational efficiency, and adaptability to various environmental conditions. As Putra et al. [3] demonstrated, marker-based systems can achieve landing accuracies within 34.1 cm compared to 121.1 cm with GPS alone – an 87% improvement that enables applications requiring high precision.

While several reviews have addressed UAV navigation and control aspects, a comprehensive, up-to-date examination of vision-based autonomous landing systems remains lacking. Previous surveys have either focused narrowly on specific landing technologies or have not adequately addressed the rapid developments in embedded computing, artificial intelligence, and multi-sensor fusion that have transformed the field in recent years.

This review aims to fill this gap by providing a systematic, comprehensive analysis of vision-based autonomous UAV landing systems, emphasising fiducial marker-based approaches. Our analysis encompasses the full spectrum of technological aspects – from marker design and detection algorithms to embedded hardware solutions and regulatory considerations.

The organisation of this paper follows a logical progression from foundational concepts to advanced implementations and future directions. Section 2 outlines our methodology for this review. Section 3 examines the evolution of UAV landing technologies and their respective advantages and limitations. Section 4 provides an in-depth analysis of fiducial marker-based landing systems, including design considerations, detection algorithms, and performance metrics. Section 5 explores hardware implementation aspects, focusing on embedded AI accelerators for real-time vision processing. Section 6 discusses multi-sensor fusion. Section 7 discusses emerging trends and future directions. Section 8 addresses regulatory frameworks, safety considerations, and technology transfer challenges. Finally, section 9 concludes the paper and suggests directions for future research.

2 Review Methodology

2.1 Research Questions and Scope

This review was guided by several key research questions designed to provide a comprehensive understanding of vision-based autonomous UAV landing systems:

1. What are the relative advantages and limitations of different vision-based autonomous landing approaches compared to traditional methods?
2. How do various fiducial marker designs and detection algorithms perform under different environmental conditions?
3. What embedded hardware solutions enable real-time vision processing on resource-constrained UAV platforms?
4. How do multi-sensor fusion approaches improve landing reliability and accuracy?
5. What are the emerging trends and future directions in vision-based autonomous landing research?
6. What regulatory frameworks and safety considerations apply to autonomous UAV landing systems?

The scope of this review encompasses vision-based autonomous landing systems for unmanned aerial vehicles, with particular focus on fiducial marker-based approaches. We excluded studies focused exclusively on UAV navigation without landing components and those addressing fully manual landing systems.

2.2 Search Strategy and Paper Selection

We conducted a systematic search in Scopus. The search was performed using combinations of key terms: “UAV” OR “drone” OR “unmanned aerial vehicle” AND “landing” OR “autonomous landing” AND “vision” OR “visual” OR “camera” OR “marker” OR “fiducial” OR “detection” AND “algorithm” OR “system” OR “technique” OR “approach”.

The inclusion criteria were as follows:

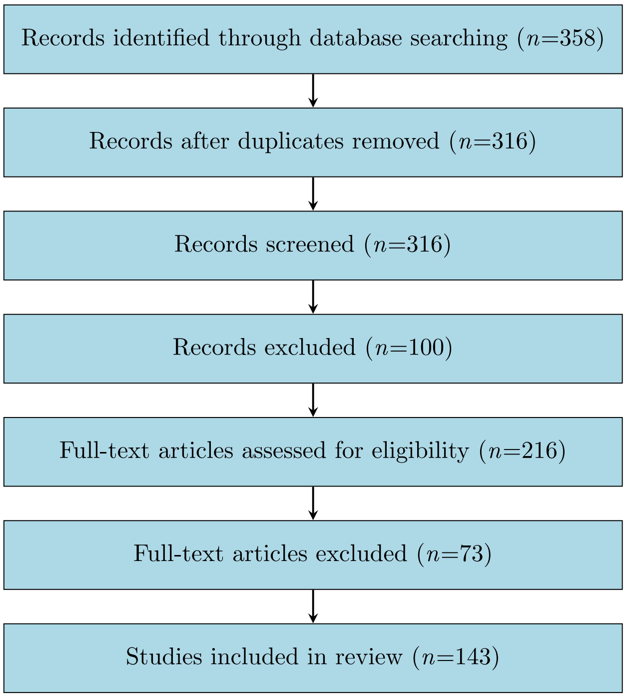


Fig. 1 PRISMA flow diagram of the paper selection process

- studies published between January 2018 and April 2025;
- peer-reviewed journal articles, conference papers, or technical reports;
- studies focusing on vision-based autonomous landing systems for UAVs;
- studies providing empirical results, technical descriptions, or systematic comparisons.

Our initial search yielded 358 potentially relevant papers. After removing duplicates and applying the inclusion criteria, 216 papers remained. Following a detailed screening of abstracts and full texts, we selected 143 papers for this review. Figure 1 illustrates the paper selection process using a PRISMA flow diagram.

2.3 Data Extraction and Analysis

From each selected paper, we extracted the following information:

- publication details (authors, year, outlet);
- landing approach classification;
- marker design (if applicable);
- detection algorithms and techniques;
- hardware implementation details;
- environmental testing conditions;
- performance metrics and results;
- limitations and future work.

Data analysis followed a narrative synthesis approach, organising findings thematically to address the research questions. Quantitative comparisons were conducted where sufficient data were available across studies. Figure 2 visually represents our methodological approach.

2.4 Classification of Approaches

Based on our analysis, we classified vision-based autonomous landing systems into the following categories:

1. Marker-based systems (fiducial markers, natural feature markers).
2. Markerless systems (direct landing site recognition).
3. Hybrid systems (combining multiple approaches).

Further sub-classifications were made based on:

- sensor configuration (monocular, stereo, RGB-D);
- detection algorithms (traditional CV, deep learning);
- hardware implementation (CPU, GPU, FPGA, dedicated accelerators).

This classification framework provides the structure for our analysis in the following sections.

3 Evolution of UAV Landing Technologies

3.1 Traditional Landing Methods and Their Limitations

The evolution of UAV landing technologies reflects the increasing demands for autonomy, precision, and reliability in diverse operational scenarios. Traditional landing methods encompass three primary approaches: manual control, GPS-guided landing, and radio-based systems. Each approach has distinct advantages and limitations that have influenced the development of vision-based alternatives.

Manual landing, controlled by human operators via remote interfaces, offers flexibility but suffers from human error susceptibility, line-of-sight requirements, and operator skill dependence. As Minohara [4] demonstrated, even experienced pilots struggle with precise landings on moving platforms or in low-visibility conditions. Operator fatigue and attentional limitations further compromise safety during extended operations. The operational parameters of manually controlled landings vary significantly among operators, with accuracy deviations of 1–3 meters reported by Wubben et al. [5], making this approach unsuitable for applications requiring consistent precision.

GPS-guided landing systems have partially addressed the limitations of manual control by providing autonomous

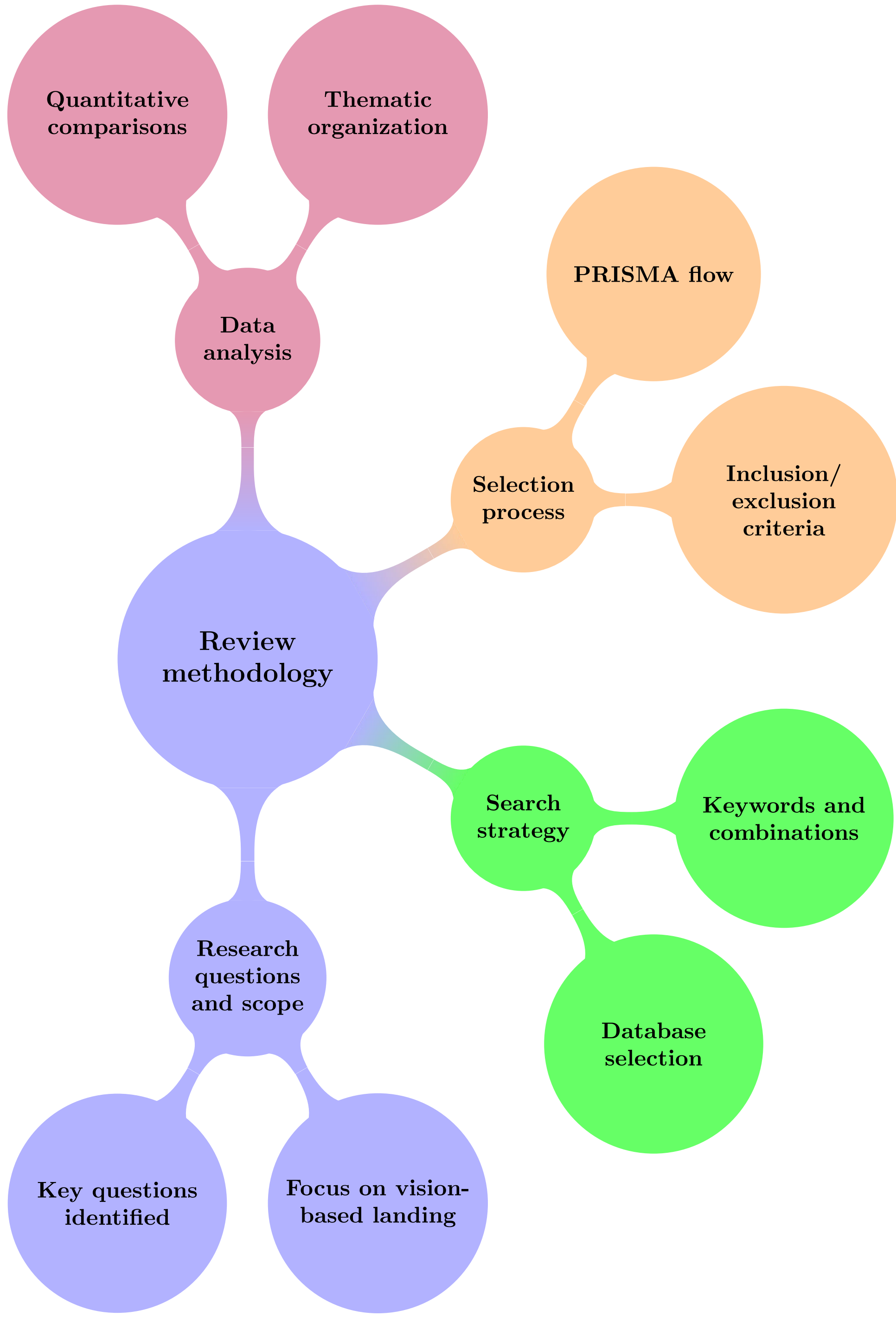


Fig. 2 Methodological approach for the systematic review

navigation capabilities. However, these systems face significant challenges in GPS-denied environments such as urban canyons, dense forests, or indoor settings where satellite signals are obstructed or degraded. Tsintotas et al. [6] reported GPS signal loss issues in mountainous environments, while Li et al. [7] documented accuracy limitations of ± 2.5 m even under optimal conditions – insufficient for precise operations on small landing pads or moving platforms. GPS spoofing and jamming vulnerabilities add further concerns for security-sensitive applications, as highlighted by Khan et al. [8].

Radio-based landing systems, including instrument landing systems (ILS) and radio beacons, provide reliable guidance in controlled environments but require substantial ground infrastructure. These systems struggle in unstructured environments and face interference issues in complex radio

Table 1 Comparative analysis of traditional UAV landing methods

Landing method	Advantages	Limitations	Reported accuracy
Manual control	Flexible across environments; adaptive to unexpected situations; no specialised equipment required	Human error susceptibility; line-of-sight required; operator skill dependent; fatigue issues	1–3 m deviation [5]
GPS-guided	Autonomous operation; global coverage; moderate cost; mature technology	Limited in GPS-denied areas; signal degradation in urban/indoor settings; vulnerable to jamming/spoofing	±2.5 m in optimal conditions [7]
Radio-based systems	Weather-independent operation; consistent in controlled environments; good range	Requires ground infrastructure; interference issues; limited in unstructured environments	±1.8 m with optimal setup [9]

environments. According to An et al. [9], radio-frequency (RF) signal-based landing systems offer range advantages but suffer from significant accuracy degradation in cluttered environments due to multipath effects.

Table 1 summarises the advantages and limitations of traditional landing approaches based on quantitative assessments from the literature.

These limitations have driven the development of vision-based systems that can operate autonomously in GPS-denied environments with higher precision and adaptability.

3.2 Transition to Vision-Based Approaches

Increasing demands for precision have driven the transition from traditional to vision-based landing approaches, the need for autonomy in diverse environments, and technological advances in sensors and computing. Vision-based systems leverage optical sensors and computer vision algorithms to perceive and interpret landing environments, enabling autonomous decision-making without relying on external navigation infrastructure.

Early vision-based systems, developed in the early 2000s, primarily used simple optical flow techniques to estimate motion parameters and altitude during landing. These systems, as documented by Conte and Doherty [10], provided basic landing capabilities but struggled with environmental variations and lacked robustness. The evolution of computer vision algorithms and the introduction of machine learning techniques dramatically improved the capabilities of vision-based systems over the following decades.

A significant milestone in vision-based landing systems was developing and refining fiducial marker detection approaches. As Huang et al. [11] demonstrated, fiducial markers provide clear visual references that can be detected and tracked with high precision, enabling accurate pose estimation relative to the landing site. These systems have progressively improved in terms of detection range, accuracy, and robustness to environmental variations.

Parallel developments in computer hardware, particularly in embedded systems and edge computing, have further accelerated the adoption of vision-based approaches. The availability of compact, energy-efficient computing platforms capable of real-time image processing has addressed many practical implementation challenges that previously limited vision-based systems. Ma [12] documented the significant performance improvements achieved through SoC-based acceleration methods for UAV runway detection algorithms, enabling real-time processing of 20 frames per second – nearly 20 times faster than CPU-only implementations.

The comparative advantages of vision-based systems over traditional methods are substantial. Putra et al. [3] reported an 87% improvement in landing accuracy using an ArUco marker-based system compared to GPS-alone approaches. Similarly, Kurdel et al. [13] demonstrated successful precision landings in mountainous areas where GPS signals were unreliable, with a 95% success rate in simulation tests. These advancements have expanded the applicability of autonomous UAV systems to previously challenging scenarios, including moving platforms, unstructured environments, and GPS-denied areas.

3.3 Classification and Taxonomy of Vision-Based Landing Systems

Vision-based landing systems can be classified according to multiple dimensions, including sensing modalities, marker utilisation, processing approaches, and landing target characteristics. Understanding this taxonomy is essential for comparing different approaches and identifying their strengths and limitations. Figure 3 presents a comprehensive taxonomy based on our literature analysis.

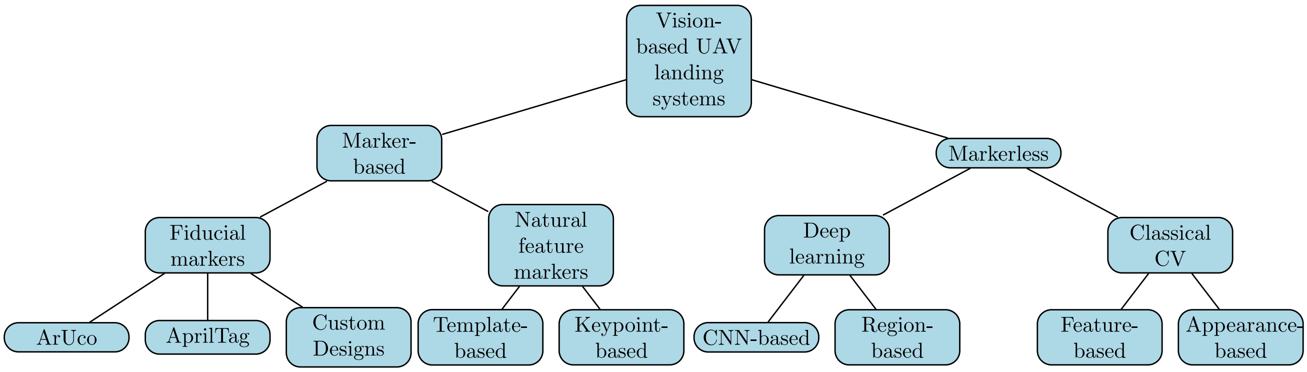


Fig. 3 Taxonomy of vision-based UAV landing systems

Marker-based systems utilise predefined visual patterns (fiducial markers) or distinctive natural features to provide position and orientation estimation reference points. *Fiducial markers*, such as ArUco, AprilTag, and custom designs, offer high detection reliability and precise pose estimation capabilities. Wubben et al. [5] demonstrated that ArUco-based systems can achieve landing accuracies within 11 cm of the target position, significantly outperforming traditional approaches. *Natural feature markers* leverage existing environmental elements with distinctive visual characteristics but may be less reliable in varying conditions.

Markerless systems directly recognise suitable landing sites without predefined visual references. These systems typically employ either *classical computer vision techniques* or deep learning approaches to analyse scene features and identify landing areas. *Deep learning-based markerless systems* have shown promising results in recent years, with Saldiran et al. [14] reporting successful autonomous emergency landings on unknown terrain using point cloud evaluation for landing site selection.

Within these categories, systems can be further differentiated based on their sensing configuration:

1. *Monocular systems* use a single camera for visual perception, offering simplicity and low weight but limiting depth perception capabilities.
2. *Stereo vision systems* employ paired cameras to enable depth estimation through triangulation, providing more robust 3D perception but requiring additional calibration and processing.
3. *RGB-D systems* combine RGB cameras with depth sensors (e.g., structured light, ToF) to directly measure depth information, enhancing environmental perception but potentially increasing system complexity and cost.

Processing approaches also vary significantly among vision-based systems:

1. *Traditional computer vision approaches* use algorithmic techniques like image filtering, feature extraction, and geometric calculations to process visual information.
2. *Machine learning approaches*, particularly deep learning, leverage trained models to recognise patterns and extract meaning from visual data, often showing greater robustness to environmental variations.
3. *Hybrid approaches* combine elements of both traditional and learning-based methods to leverage their complementary strengths.

Landing targets add another dimension to the classification:

1. *Static targets* remain fixed during the landing process, simplifying trajectory planning and control.
2. *Moving targets* (e.g., vehicles, vessels) require additional tracking and prediction capabilities to coordinate the landing manoeuvre.
3. *Uncooperative targets* lack specific landing aids or may be unaware of the landing attempt, requiring enhanced perception and decision-making capabilities.

This taxonomy provides a framework for understanding the diverse approaches to vision-based autonomous landing and contextualising the detailed technical discussions in subsequent sections.

Table 2 presents a comprehensive comparative analysis of the major classes of vision-based landing systems across key performance and implementation criteria to facilitate informed decision-making for system designers and researchers. This high-level comparison synthesises findings from our literature analysis to provide practical guidance for selecting appropriate approaches based on specific operational requirements and constraints.

Fiducial marker-based systems offer the highest precision (2-34 cm landing accuracy) but require infrastructure installation, limiting operational flexibility. Conversely, markerless deep learning approaches provide greater flexibility with

Table 2 Comprehensive comparison of vision-based UAV landing system classes

Criteria	Marker-based (fiducial)	Marker-based (natural features)	Markerless (Deep learning)	Markerless (classical CV)	Hybrid systems
Precision/ accuracy	*Very high* 2-34 cm [3, 15]	*Medium* 20-100 cm (feature dependent)	*Medium-high* 10-50 cm [16]	*Low-medium* 50-200 cm (terrain dependent)	*High* 5-30 cm [17]
Implementation cost	*Low-medium* $500-2K for markers + standard cameras	*Low* No infrastructure needed	*Medium* Training costs + inference hardware	*Low* Software only	*Medium-high* Multiple sensors/algorithms
Environmental robustness	*Medium-high* Depends on marker design	*Low-medium* Sensitive to feature changes	*High* Learns from diverse conditions	*Low* Algorithm-specific limitations	*Very high* Multimodal redundancy
Hardware requirements	*Low* Standard RGB camera sufficient	*Medium* May need higher resolution	*Medium-high* GPU preferred for real-time	*Low-medium* Standard cameras	*High* Multiple sensor types
Computational requirements	*Low-medium* Traditional CV: low ML-enhanced: Medium	*Medium* Feature matching complexity	*High* 5-20 TOPS for inference	*Medium* 1-5 TOPS typical	*Medium-high* Fusion overhead
Operational flexibility	*Low* Requires marker installation	*Medium* Limited to feature-rich environments	*Very high* Any suitable terrain	*High* No infrastructure needed	*High* Adaptive to conditions
Setup complexity	*Medium* Marker placement and calibration	*Low* Feature selection only	*High* Training data collection and model development	*Low* Algorithm tuning	*High* Multi-sensor integration and calibration
Maintenance requirements	*Low* Periodic marker inspection	*Medium* Feature stability monitoring	*Medium* Model updates needed	*Low* Minimal updates	*High* Multiple components
Scalability	*High* Standardized markers	*Low* Site-specific features	*Medium* Transfer learning possible	*Medium* Algorithm dependent	*Low* Complex integration
Technology maturity	*Mature* Widely deployed	*Developing* Limited deployment	*Emerging* Research phase	*Mature* Well-established	*Developing* Custom solutions
Typical applications	Package delivery; inspection return; warehouse operations	Emergency landing; exploration; mapping operations	Urban operations; emergency response; military applications	Agricultural monitoring; open terrain landing; basic autonomy	High-value operations; all-weather missions; research platforms

moderate precision (10-50 cm), suitable for operations in unstructured environments.

Traditional marker-based systems using classical computer vision offer the most cost-effective solution for applications with fixed landing sites, requiring only $500-2,000 for markers and standard cameras. Deep learning approaches incur higher initial costs for training and specialised hardware but eliminate ongoing infrastructure maintenance.

Hybrid systems demonstrate superior robustness through multimodal redundancy, achieving high reliability across diverse conditions. Single-modality approaches show varying robustness, with deep learning systems exhibiting better adaptability to environmental variations through learned representations than classical algorithms' fixed parameters.

A clear hierarchy emerges in computational demands, with traditional marker detection requiring only 0.1-1 TOPS, classical markerless approaches needing 1-5 TOPS, and deep learning systems demanding 5-20 TOPS for real-time operation. This directly impacts platform selection and power consumption considerations.

Fiducial marker-based systems represent the most mature technology with widespread commercial deployment, while deep learning approaches remain primarily in research phases. This maturity gap influences risk assessment for operational deployments, with hybrid approaches offering a balanced compromise between innovation and reliability.

System designers should consider these trade-offs holistically, matching landing system characteristics to specific operational requirements. For high-precision, repetitive operations at fixed locations (e.g., warehouse logistics), fiducial markers provide optimal cost-performance ratios. For diverse, unpredictable environments (e.g., emergency response), markerless or hybrid approaches offer necessary flexibility despite higher complexity and cost. The ongoing evolution of edge computing capabilities and algorithm efficiency continues to shift these trade-offs, gradually reducing the computational penalties of more sophisticated approaches.

4 Fiducial Marker-Based Landing Systems

4.1 Marker Design Considerations

Fiducial marker-based landing systems rely on detecting and tracking predefined visual patterns to estimate the UAV's position and orientation relative to the landing site. The design of these markers significantly impacts the system's performance in terms of detection range, accuracy, and robustness to environmental variations. Our analysis reveals several critical design considerations that influence marker effectiveness.

Marker geometry constitutes a fundamental design aspect with significant performance implications. Square markers, such as ArUco and AprilTag, dominate contemporary implementations due to their geometric simplicity and robust corner detection properties. Putra et al. [3] demonstrated that square ArUco markers enable precise pose estimation through reliable corner detection, achieving landing accuracies of 34.1 cm in field tests. Circular markers, by contrast, offer rotational invariance advantages but may provide less precise pose estimation. Claro et al. [18] introduced a novel multimodal marker called ArTuga that achieved position estimation accuracy of 0.0060 m with a standard deviation of 0.0003 m at 1 m height through a hybrid design combining square and circular elements.

The size-to-detection range relationship represents another critical consideration. Optimal marker size depends on the expected detection altitude, camera specifications, and required landing precision. Lebedev et al. [19] demonstrated that marker size directly influences the maximum detection range, with larger markers detectable from higher altitudes but potentially reducing precision during the final landing phase. They reported landing errors of approximately 20 mm in simulation and 21.2 mm in real-world tests using appropriately sized ArUco markers. Khazetdinov et al. [15] addressed this limitation through the embedded ArUco (e-ArUco) design, which enables robust detection across a wide range of distances by nesting markers at different scales, achieving an average landing accuracy of 2.03 cm in virtual experiments.

Colour and contrast characteristics significantly impact detection reliability across varying lighting conditions. High-contrast black and white markers remain prevalent due to their robustness under different illumination scenarios. However, Tummala et al. [20] found that detection accuracy varies significantly with brightness levels, showing improved performance at both extremely high and low brightness levels compared to intermediate levels. This non-linear relationship suggests that adaptive approaches to marker design might be necessary for operations in varying lighting conditions. Lin et al. [21] specifically addressed low-illumination conditions, developing a system capable of detecting markers in night-time environments with an average luminance of 5 lx without requiring active illumination.

Information density and error correction capabilities represent a balance between uniqueness and robustness. Higher bit densities enable more unique identifiers but may reduce detection reliability under adverse conditions. Romero-Ramire et al. [22] demonstrated that fractal markers with hierarchical information structures can maintain detection capabilities under severe occlusions, addressing a significant limitation of traditional designs. They reported improved detection range and occlusion resistance compared to standard markers, enabling reliable pose estimation even when portions of the marker are obscured.

Environmental adaptability features have emerged to address specific operational challenges. Anikin et al. [23]

Table 3 Comparative analysis of fiducial marker designs for UAV landing

Marker type	Advantages	Limitations	Optimal conditions	Reported accuracy
ArUco	Fast detection; dictionary-based; good occlusion resistance	Performance degradation at extreme angles; limited detection range	Good lighting; moderate distances; limited distortion	11-34 cm [3, 5]
AprilTag	High accuracy; robust to lighting variations; error correction	Computationally intensive; limited dictionary size	Stable lighting; clear view; static conditions	≈5 cm [25]
Embedded ArUco (e-ArUco)	Wide detection range; scale invariance; nested structure	Complex detection logic; higher computational requirements	Multi-scale operations; variable approach distances	2.03 cm [15]
ArTuga	Multimodal sensing; day/night operation; high precision	Complex hardware; higher cost; specialized detection	Various lighting; challenging environments	0.6 cm at 1 m height [18]
Fractal markers	Occlusion resistance; extended range; hierarchical information	Complex detection; higher false positives at distance	Partially obstructed views; variable distances	Not specified [22]

investigated the effects of environmental conditions, including light, fog, wind, and precipitation, on UAV landing accuracy, finding that wind most significantly impacted landing time while having minimal effect on accuracy. Choi et al. [24] specifically examined fiducial marker detection from rotorcraft under adverse environmental conditions, documenting performance impacts under variations in temperature, illumination, wind speed, and precipitation. These studies have informed the development of markers with enhanced environmental robustness.

Table 3 presents a comparative analysis of common marker designs based on quantitative assessments from the literature.

The evolution of marker designs reflects an ongoing effort to address the diverse challenges of real-world deployment scenarios. Modern designs increasingly incorporate elements that enhance robustness to environmental variations, extend detection ranges, and improve accuracy across operational phases. Future developments will likely continue this trajectory, with potential advances in adaptive markers that can dynamically adjust their properties based on environmental conditions and detection requirements.

4.2 Detection Algorithms and Techniques

Fiducial marker detection algorithms form the computational core of marker-based landing systems, translating raw image data into precise position and orientation estimates. These algorithms have evolved significantly, from simple template matching approaches to sophisticated multi-stage pipelines incorporating machine learning elements. Our analysis identifies several algorithmic categories with distinct characteristics and performance profiles.

Traditional computer vision approaches remain prevalent due to their computational efficiency and deterministic behaviour. These methods typically employ a pipeline that includes preprocessing, feature extraction, marker identification, and pose estimation stages. Lebedev et al. [19] demonstrated that traditional ArUco detection algorithms can achieve landing accuracies of approximately 20 mm in controlled environments using this approach. The sequential processing nature of these algorithms enables clear reasoning about failure modes and performance characteristics, facilitating reliable implementation on resource-constrained platforms.

Deep learning-based detection methods have emerged as powerful alternatives, offering improved robustness to environmental variations at the cost of increased computational demands. Khan et al. [26] developed the SafeSpace MFNet, a multi-feature drone detection network achieving 99.8% precision for bird detection and 97.2% for UAV detection through a combination of feature enhancement and attention mechanisms. Similarly, Jin et al. [27] demonstrated a CNN-based discriminant approach for autonomous landing marker detection, achieving 25 fps processing speed with 720p resolution video on an onboard computer. These learning-based approaches have shown particular value in challenging conditions where traditional methods struggle, such as varying lighting, partial occlusions, or complex backgrounds.

Hybrid approaches combine elements of traditional and learning-based methods to leverage their complementary strengths. Lin et al. [21] proposed a hierarchical method consisting of a decision tree with an associated lightweight CNN for coarse-to-fine landing marker localisation in low-illumination environments. Similarly, Cheng et al. [28] developed an intelligent detection approach for structural monitoring combining frequency symmetrised dot pattern (FSDP) features with deep convolutional neural networks (DCNNs). These hybrid approaches often achieve superior performance-efficiency trade-offs compared to pure implementations of either paradigm.

The temporal dimension introduces additional complexities and opportunities in detection algorithms. Raxit et al. [29] developed YoloTag, a real-time fiducial marker-based localisation system using a lightweight YOLOv8 object detector combined with perspective-n-point algorithms and higher-order Butterworth filtering to suppress noise in trajectory tracking. This approach leverages temporal consistency to enhance detection reliability and smoothness. Similarly, Koubaa et al. [30] proposed AERO, a multi-stage deep learning module combining object detection (YOLOv4/YOLOv7) and tracking (DeepSort) with TensorRT accelerators to capture objects with high accuracy and reduced false positive rates.

Beyond detection algorithms, precise control during the landing phase is equally critical. Recent work in trajectory tracking control, such as the PSO-optimised controllers proposed by Kedir and Abdissa [31] and Wendemagegn et al. [32], demonstrates the potential for integrating advanced control methods with vision-based detection systems to achieve more accurate landing performance.

Environmental adaptation capabilities have become increasingly important as systems encounter diverse operational conditions. Gharsa et al. [33] developed a vision-based landing system capable of safely landing UAVs in GPS-denied scenarios through adaptive parameter adjustment. Similarly, Wu et al. [34] demonstrated online adaptation to label distribution shifts without requiring ground truth observations, enabling continuous adaptation to changing environmental conditions. These adaptive approaches enable robust performance across varying scenarios without requiring manual reconfiguration.

Table 4 presents a comparative analysis of detection algorithms based on performance metrics reported in the literature.

Table 4 Comparative analysis of marker detection algorithms for UAV landing

Algorithm approach	Processing speed	Accuracy	Environmental robustness	Platform power	Estimate energy efficiency*	Reference
Traditional CV (ArUco)	N/S	11 cm offset	Moderate	∼5 W	High	Wubben et al. [5]
CNN-based	17.5 ms/frame	F-measure: 95.6%	High	∼15 W	Medium	Jin et al. [27]
YOLOv5-based	Real-time	mAP@0.5: 80.9%	High	10-30 W†	Low-medium	Zhang et al. [35]
Hierarchical	19.8 Hz	High	Excellent (5 lx)	∼10 W	Medium	Lin et al. [21]
Multi-stage	15.5 fps	FPR: 0.7%	High	10-30 W	Low	Koubaa et al. [30]

*Estimated based on platform typical power consumption; †Deployment platform dependent

The lack of explicit energy efficiency metrics (TOPS/W) in the reviewed papers highlights a critical gap in the literature. While processing speed and accuracy are well-documented, power consumption measurements are notably absent. Future research should include standardised energy efficiency benchmarks to enable meaningful comparisons for resource-constrained UAV platforms. Based on typical platform power consumption, we estimate that traditional computer vision approaches on low-power processors (e.g., Raspberry Pi) likely achieve the highest energy efficiency, while deep learning approaches on GPU-accelerated platforms trade efficiency for enhanced accuracy and robustness. Actual measurements would be valuable for platform-specific algorithm selection in practical UAV deployments.

The optimal algorithm selection depends on specific application requirements, environmental conditions, and hardware constraints. Traditional methods offer deterministic performance with lower computational requirements, making them suitable for resource-constrained platforms. Deep learning-based approaches enhance robustness in challenging environments but demand more computational resources. Hybrid and multi-stage pipelines potentially offer the best compromise for practical implementations, combining efficiency with adaptability.

4.3 Performance Evaluation Metrics and Benchmarks

Rigorous performance evaluation is essential for comparing different marker-based landing systems and assessing their suitability for specific applications. Our analysis reveals a diverse set of metrics used across the literature, reflecting the multifaceted nature of landing system performance. These metrics can be categorised into detection performance, pose estimation accuracy, temporal characteristics, and robustness measures.

Detection performance metrics quantify the system's ability to identify markers in various conditions correctly. Khan et al. [26] used precision, recall, and mean average precision (mAP) to evaluate drone detection algorithms, reporting values of 99.8% precision for bird detection and 97.2% precision for UAV detection with their best-performing model. Similarly, Zhang et al. [35] reported mAP@0.5 of 80.9% for their Rotator-YOLOv5 algorithm in UAV aerial images. These metrics provide valuable insights into the reliability of marker detection across different scenarios.

Pose estimation accuracy directly impacts landing precision and is typically measured through position and orientation errors relative to ground truth. Claro et al. [18] reported position estimation accuracy of 0.0060 m with a standard deviation of 0.0003 m at 1 m height, and precise landing with an average deviation of 0.027 m from the target. Khazetdinov et al. [15] demonstrated an average landing accuracy of 2.03 cm with a standard deviation of 1.53 cm in virtual environments using e-ArUco markers. These metrics directly correlate with the system's ability to execute precise landings in real-world scenarios.

Temporal characteristics capture the system's dynamic performance, including processing speed, latency, and adaptation rate. Koubaa et al. [30] reported an average inference speed of 15.5 frames per second (FPS) on a Jetson Xavier AGX edge device, while Jin et al. [27] achieved 25 fps with 720p resolution. Elamin et al. [36] documented latencies of 5–10 ms per event batch and 10–20 ms for frame updates in an event-based visual-inertial odometry system, demonstrating real-time performance on resource-constrained platforms. These temporal metrics are crucial for assessing the system's ability to handle dynamic scenarios, such as landing on moving platforms.

Robustness measures quantify the system's reliability across varying environmental conditions. Tovanche-Picon et al. [37] evaluated landing system performance in both static and dynamic scenarios, reporting a 99% success rate in static scenarios and 87% in dynamic cases using a virtual evaluation pipeline. Park et al. [17] tested a fiducial marker-based

Table 5 Key performance metrics for marker-based UAV landing systems

Metric category	Specific metrics	Typical values	References
Detection performance	Precision, Recall, F1 score, mAP, Detection rate	Precision: 90-99% mAP@0.5: 80-98%	Khan et al. [26], Zhang et al. [35]
Pose estimation accuracy	Position error, Orientation error, Landing deviation	Position: 0.6-34 cm Heading: 1-3°	Putra et al. [3], Claro et al. [18]
Temporal characteristics	Processing speed (fps), Latency, Convergence time	Speed: 15-60 fps Latency: 5-50 ms	Jin et al. [27], Koubaa et al. [30]
Robustness measures	Success rate, Error under disturbance, Environmental variation	Success: 87-99% Error with disturbance: <10 cm	Park et al. [17], Tovanche-Picon et al. [37]

autonomous landing system in simulation and flight tests, achieving landing position errors up to 2.70 cm radius in simulation and within 9.470 cm radius in flight tests with disturbances. These metrics provide insights into the system's practical reliability in real-world deployment scenarios.

The evaluation methodologies employed in the literature vary significantly, complicating direct comparisons between different systems. Kurdel et al. [13] used a simulation with artificially intelligent UAV precision landing in mountainous areas, reporting successful navigation to the landing point using FDLS signals with an over 95% success rate. Nicholson et al. [25] employed motion capture systems for ground truth measurements in hovering and landing flight tests, conducting fifteen successful autonomous landings in scaled sea states as high as six. These diverse methodologies reflect the complexity of comprehensive landing system evaluation.

Standardised benchmarks for marker-based landing systems remain limited, with most studies employing custom evaluation procedures tailored to their specific implementation and target application. The lack of standardised benchmarks complicates cross-study comparisons and may hinder systematic progress in the field. Chang et al. [38] attempted to address this gap by proposing evaluation metrics including path length, deviation rate, and exploration efficiency for UAV navigation strategies, providing a potential framework for more standardised evaluations.

Table 5 summarises the key performance metrics used in recent studies of marker-based landing systems.

Future advancements in performance evaluation should focus on developing standardised benchmarks and evaluation methodologies that enable meaningful comparisons across different systems and approaches. Such standardisation would facilitate more systematic progress in the field and provide clearer guidance for system selection in practical applications.

4.4 Environmental Factors Affecting Performance

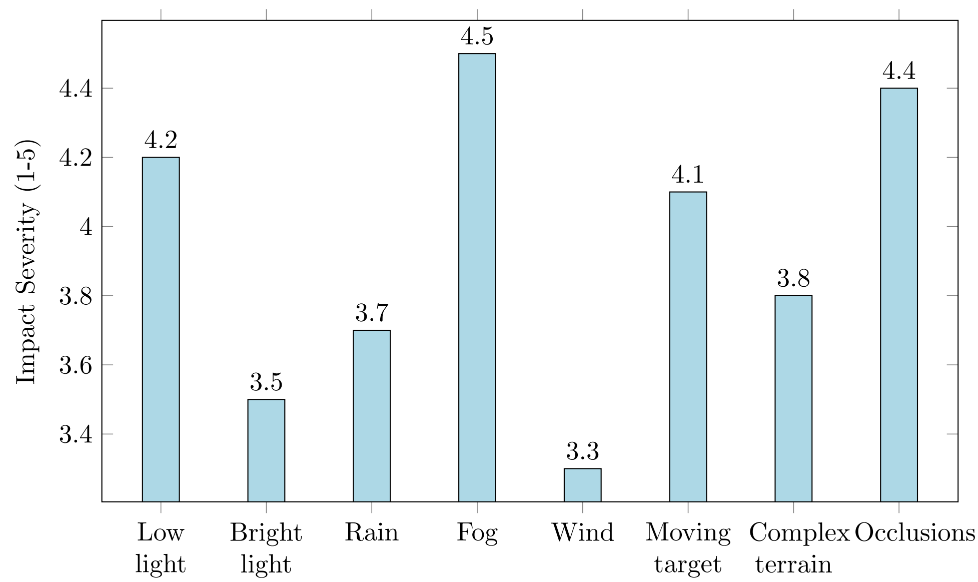
The performance of marker-based landing systems is significantly influenced by the environmental conditions in which they operate. Our analysis identifies several key environmental factors that impact system performance, including illumination variations, weather conditions, terrain characteristics, and dynamic elements. Understanding these influences is crucial for designing robust systems capable of reliable operation across diverse scenarios.

Illumination variations represent one of the most significant challenges for vision-based systems. Lin et al. [21] specifically addressed low-illumination conditions, developing a system capable of operating in outdoor nighttime scenarios with an average luminance of 5 lx without requiring active illumination. They employed a model-based enhancement scheme to improve image quality and brightness, combined with a hierarchical detection method to achieve robust performance in challenging lighting conditions. Tummala et al. [20] investigated the impact of brightness variations on YOLOv8 object detection, finding that detection accuracy varied significantly with brightness levels, with higher performance at both extremely low and high brightness levels compared to intermediate values. This non-linear relationship suggests the need for adaptive approaches to handle varying illumination conditions.

Weather conditions, including precipitation, fog, and wind, can severely impact detection reliability and landing accuracy. Anikin et al. [23] conducted experiments in the Gazebo simulation environment to study the influence of weather conditions on autonomous landing, finding that wind had the most significant impact on landing time while having a limited effect on accuracy. Choi et al. [24] specifically examined fiducial marker detection under adverse environmental conditions, including temperature variations, illumination changes, wind, and precipitation, documenting the complex interactions between these factors and system performance. These studies highlight the importance of resilient detection algorithms and control systems capable of compensating for weather-induced disturbances.

Terrain characteristics influence both the visibility of markers and the feasibility of safe landings. Chen et al. [16] addressed emergency landing on unknown fields using depth-enhanced graph structures, achieving accurate landing

Fig. 4 Relative impact of environmental factors on marker-based landing system performance (based on literature analysis, scale 1-5 where 5 represents most severe impact)



site selection in unstructured environments through topology information extraction and 3D optimisation. Similarly, Saldiran et al. [14] developed an autonomous emergency landing system for unknown terrain using LIDAR-based point cloud evaluation to identify safe landing sites based on slope, roughness, and peak distance differences. These approaches demonstrate the importance of environmental perception beyond marker detection for comprehensive landing systems.

Dynamic elements such as moving platforms, obstacles, and changing scenes introduce additional complexities. Yang et al. [39] developed a hybrid camera array-based system for UAV landing on moving UGVs in GPS-denied environments, combining a wide field of view and depth imaging with motion state estimation to enable precise landings on mobile platforms. Tovanche-Picon et al. [37] evaluated autonomous landing in populated areas using photo-realistic virtual environments, achieving a 99% success rate in static scenarios and 87% in dynamic cases through computer vision and convolutional neural networks for safe landing area detection. These studies highlight the importance of temporal reasoning and predictive capabilities in dynamic environments.

The combined effects of multiple environmental factors can create particularly challenging scenarios that exceed the capabilities of simpler systems. Troll et al. [40] developed an indoor localisation system for quadcopters in industrial environments using ArUco markers, LiDAR, and sensor fusion through Extended Kalman Filtering to achieve reliable positioning despite complex environmental conditions. Similarly, Goricanec et al. [41] proposed an Augmented Artificial Potential Field (AAPF) approach for collision-free trajectory following in unknown environments, demonstrating the system's ability to handle diverse obstacles and local minima problems. These integrated approaches represent the state of the art in addressing complex environmental challenges.

Figure 4 illustrates the relative impact of different environmental factors on marker-based landing system performance based on our literature analysis.

Mitigating these environmental challenges requires a combination of robust hardware, adaptive algorithms, and multimodal sensing approaches. Future advancements will likely focus on developing systems with greater environmental awareness and adaptability, leveraging techniques from artificial intelligence to adjust detection and control parameters based on environmental conditions dynamically. Such advances would significantly enhance the practical utility of marker-based landing systems across diverse operational scenarios.

5 Hardware Implementation and Edge Computing

5.1 Resource Constraints in UAV Platforms

UAV platforms impose significant resource constraints on vision-based landing systems, necessitating careful hardware selection and optimisation. These constraints encompass computational capacity, power consumption, weight limitations, and thermal considerations – all of which directly impact the feasibility and performance of onboard vision processing. Understanding these constraints is essential for developing practical, deployable landing systems.

Computational constraints represent a primary challenge for real-time vision processing on UAVs. Van Beeck et al. [42] highlighted that the computational complexity of

Table 6 Typical resource constraints across UAV classes for vision processing systems

UAV class	Computational budget	Power budget	Weight budget	References
Nano UAVs (<250 g)	0.1-1 TOPS	1-3 W	10-30 g	Ye et al. [45]
Mini UAVs (250 g-2k g)	1-5 TOPS	3-10 W	50-200 g	Gama et al. [43]
Small UAVs (2-25 kg)	5-20 TOPS	10-50 W	200-500 g	Troll et al. [40]
Medium UAVs (>25 kg)	20+ TOPS	50-150 W	0.5-2 kg	Huang et al. [44]

state-of-the-art computer vision algorithms often conflicts with the need for real-time operation on resource-limited hardware. This tension becomes particularly acute for deep learning-based approaches, which typically require substantial computational resources. Gama et al. [43] noted that deep neural network (DNN) computational and power requirements exceed the budget for small-sized UAVs due to onboard memory constraints, necessitating specialised optimisation techniques. These computational limitations directly impact algorithm selection and implementation strategies for vision-based landing systems.

Power consumption constraints further restrict the available computing capacity for onboard vision processing. UAVs operate on battery power with limited energy reserves that must be allocated across propulsion, sensors, communication, and computing systems. Huang et al. [44] demonstrated that an edge and trustworthy AI UAV system could enhance energy efficiency by 2.7× compared to embedded GPU solutions through FPGA-based implementations, highlighting the critical importance of energy-efficient computing architectures. Ye et al. [45] similarly optimised a YOLOv5-based forest fire detection system for Raspberry Pi, achieving 50% higher inference speed (9 FPS) while reducing CPU usage, temperature, and power consumption by 35%, 25%, and 10% respectively through hardware-aware algorithm design.

Weight limitations compound these challenges by restricting the size and capacity of onboard computing hardware. Troll et al. [40] designed a quadcopter capable of carrying at least 0.5 kg additional payload for sensing and computing equipment, illustrating the tight weight budgets available for vision processing systems. These weight constraints often necessitate compact, integrated computing solutions rather than more powerful but heavier alternatives. The drive toward miniaturisation has spurred the development of increasingly capable yet compact computing platforms specifically designed for UAV applications.

Thermal considerations introduce additional complications, as compact computing systems operating at high utilisation generate significant heat that must be dissipated in the constrained UAV environment. Ye et al. [45] noted that their optimisation approach reduced CPU temperature by 25% during operation, enhancing system reliability by mitigating thermal issues. Effective thermal management is crucial for maintaining consistent performance and preventing hardware failures during extended operations, particularly in challenging environmental conditions.

Table 6 summarises typical resource constraints for different UAV classes based on data reported in the literature.

Addressing these resource constraints requires integrated approaches that optimise across computing architecture, algorithm design, and system integration. The following sections examine specific hardware platforms and acceleration techniques that enable effective vision-based landing systems within these constraints.

5.2 Embedded Computing Platforms for Vision Processing

The selection of appropriate embedded computing platforms is crucial for implementing vision-based landing systems within UAV resource constraints. Our analysis reveals several categories of platforms with distinct characteristics, advantages, and limitations. The evolution of these platforms has dramatically expanded the capabilities of onboard vision processing while maintaining compliance with UAV resource constraints.

Single-board computers (SBCs) represent a common entry point for vision processing on UAVs due to their accessibility, programmability, and moderate capabilities. Troll et al. [40] developed a UAV localisation system using Raspberry Pi in combination with PixHawk flight controllers, leveraging OpenCV for computer vision and ROS for system integration. Similarly, Jin et al. [27] demonstrated autonomous landing using an Intel NUC onboard computer, achieving 25 fps processing with 720p resolution. These general-purpose computing platforms offer flexibility and ease of development but typically provide limited performance for complex vision algorithms compared to specialised alternatives.

Mobile SoCs with integrated GPUs represent a significant advance in computing capabilities for vision-based systems. Koubaa et al. [30] implemented the AERO system using GPU-enabled edge devices to combine object detection (YOLOv4/YOLOv7) and tracking (DeepSort) with TensorRT accelerators, achieving 15.5 FPS average inference speed on a Jetson Xavier AGX. Wang et al. [46] similarly leveraged embedded GPU capabilities for their

Table 7 Comparative analysis of embedded computing platforms for UAV vision processing

Platform type	Representative systems	Performance (TOPS)	Power efficiency (TOPS/W)	Development complexity	References
Single-Board Computers	Raspberry Pi 4, Intel NUC	0.1-2	0.1-0.5	Low	Jin et al. [27], Troll et al. [40]
Mobile SoCs with GPU	NVIDIA Jetson, Qualcomm	2-32	0.5-2	Medium	Koubaa et al. [30], Wang et al. [46]
FPGA-based Solutions	Xilinx Zynq, Intel Altera	1-8*	1-5*	High	Huang et al. [44], Zhao et al. [47]
ASICs/VPUs	Google Coral, Intel Movidius	2-8*	2-10*	Medium-High	n/a
Heterogeneous	Custom multi-chip systems	5-40*	1-5*	Very High	Ma [12], Huang et al. [44]

* Varies significantly based on specific implementation and workload

FLDet lightweight detector, achieving real-time performance exceeding 52 FPS on an NVIDIA Jetson Xavier NX with only 1.2M parameters. These platforms offer substantially higher performance for parallel workloads like neural network inference while maintaining reasonable power consumption and weight characteristics.

FPGA-based solutions provide customisable hardware acceleration tailored to specific vision processing pipelines. Zhao et al. [47] proposed a scalable FPGA-based CNN accelerator for embedded systems, achieving 1.9× energy efficiency compared to previous work through OpenCL implementation. Huang et al. [44] developed an FPGA-based system architecture with neural engines, cryptographic hardware modules, and hardware protection matrices, demonstrating speedups of 2.28× to 36.9× in frames per second compared to microprocessor-based designs. These reconfigurable platforms enable efficient implementation of specific vision algorithms but typically require more specialised development expertise.

Application-specific integrated circuits (ASICs) and vision processing units (VPUs) offer the highest efficiency for specific vision tasks through dedicated hardware implementations. While less frequently mentioned in the UAV landing literature, these specialised accelerators are increasingly available as components in heterogeneous computing platforms. Their fixed functionality provides exceptional efficiency for supported operations but limits flexibility compared to more general-purpose alternatives.

Heterogeneous computing architectures combining multiple processing elements represent the state of the art for complex vision-based systems. Huang et al. [44] implemented an edge and trustworthy AI UAV system with self-adaptivity using a combination of FPGA-based neural engines and conventional processing elements. Similarly, Ma [12] developed a SoC-based acceleration method for UAV runway detection using a combination of programmable logic and general-purpose processors. These integrated approaches leverage the complementary strengths of different computing elements to achieve optimal performance within resource constraints.

Table 7 presents a comparative analysis of embedded computing platforms for vision-based landing systems based on data reported in the literature.

The selection of an appropriate computing platform depends on the specific requirements of the vision-based landing system, including algorithm complexity, real-time constraints, power budget, and development resources. Modern systems increasingly leverage heterogeneous architectures with specialised accelerators to achieve optimal performance within UAV resource constraints. Future trends point toward even greater integration of specialised accelerators, with potential advances in neuromorphic computing and other novel architectures that may further enhance the capabilities of onboard vision processing for autonomous landing systems.

5.3 Acceleration Techniques for Real-Time Vision Processing

Real-time vision processing on resource-constrained UAV platforms requires specialised acceleration techniques that optimise performance across hardware, algorithm, and system levels. Our analysis identifies several key techniques in recent landing systems, including hardware acceleration, model optimisation, algorithm adaptation, and system-level optimisation approaches.

Hardware acceleration leverages specialised computing elements to execute vision processing tasks more effi-

Table 8 Acceleration techniques for real-time vision processing on UAVs

Technique category	Specific methods	Advantages	Limitations	Reported improvements
Hardware acceleration	TensorRT, FPGA implementations, custom accelerators	Maximal performance for specific tasks; direct hardware-algorithm matching	Specialized development; reduced flexibility; higher cost	1.9-36.9× speedup [44, 47]
Model optimisation	Pruning, quantisation, knowledge distillation, efficient architectures	Platform independence; maintained flexibility; relatively simple implementation	Potential accuracy loss; algorithm-specific techniques	87-98% size reduction; 1-2% accuracy loss [46, 48]
Algorithm adaptation	Lightweight CNNs, algorithm simplification, task-specific optimisations	Preserved accuracy; maintained flexibility; algorithm-specific gains	Limited generalizability; may require algorithm redesign	Real-time performance on constrained devices [21, 43]
System-level optimisation	Pipeline optimisation, memory management, parallel processing	Integrated improvements; platform-specific optimization; synergistic gains	Complex implementation; system-specific solutions	2.28× performance gain; 35% reduced CPU usage [45, 49]

ciently than general-purpose processors. Koubaa et al. [30] employed TensorRT accelerators for deep learning inference, significantly improving processing speed and energy efficiency. Zhao et al. [47] developed a scalable FPGA-based CNN accelerator, achieving 1.9× energy efficiency through customized hardware implementation. These approaches directly match computing architecture to algorithmic requirements, enabling substantial performance improvements for specific vision tasks. However, they often require specialised development expertise and may reduce flexibility compared to software-only solutions.

Model optimisation techniques reduce the computational requirements of vision algorithms while preserving essential functionality. Wang et al. [46] developed FLDet, a family of faster and lighter detectors designed explicitly for UAVs, achieving a state-of-the-art balance between accuracy, latency, and parameter efficiency. Their approach reduced model parameters to 1.2M while maintaining real-time performance exceeding 52 FPS on embedded platforms. Similarly, Hou et al. [48] proposed a lightweight UAV object detection algorithm based on iterative sparse training, reducing weights by 98.72% and FLOPS by 90.03% with only 2.0% mAP loss. These optimisation techniques make complex vision algorithms feasible on resource-constrained platforms without requiring specialised hardware.

Algorithm adaptation approaches modify vision processing methods to match available computing resources better. Gama et al. [43] implemented CNN models such as MobileNet combined with SSD for real-time object tracking on small-sized quadrotor UAVs, employing quantisation and CMSIS-NN optimisation for low-powered ARM architectures. Lin et al. [21] developed a lightweight CNN for landing marker localisation in low-illumination environments, using a hierarchical approach to balance accuracy and computational efficiency. These adaptations maintain essential functionality while reducing resource requirements through algorithm-level modifications considering hardware characteristics.

System-level optimisations improve overall performance through integrated hardware, software, and system architecture approaches. Jiang et al. [49] employed a human-in-the-loop model pruning method with Gaussian penalty terms for ship detection, reducing model size by 87.94% with only a 1.48% accuracy decrease and improving real-time performance by 2.28 times after GPU deployment optimisation. Ye et al. [45] optimised a forest fire detection system through backbone network replacement, pruning, sparse training, and hardware acceleration, achieving higher inference speed with reduced CPU usage and power consumption. These integrated approaches often yield the most substantial improvements by addressing multiple performance bottlenecks simultaneously.

Table 8 summarises key acceleration techniques and their reported performance improvements based on data from the literature.

The most effective acceleration approaches typically combine multiple techniques across different levels, leveraging their complementary benefits to achieve optimal performance within platform constraints. Future advancements in acceleration techniques will likely focus on automated optimisation frameworks that can dynamically adapt vision processing pipelines to specific hardware capabilities and operational requirements. Such frameworks would significantly reduce development effort while maximising performance within UAV resource constraints.

5.4 Case Studies of Hardware Implementations

Examining specific case studies of hardware implementations provides valuable insights into practical approaches for vision-based landing systems across different UAV classes and application domains. These implementations demonstrate how theoretical concepts and acceleration techniques translate into functional systems capable of operating within real-world constraints. Our analysis includes case studies spanning nano/micro UAVs, small tactical UAVs, and larger platforms with diverse computational architectures.

Troll et al. [40] developed an indoor localisation system for quadcopters in industrial environments using Raspberry Pi, PixHawk flight controllers, and OpenCV. Their system employed ArUco markers for position estimation and LiDAR with Hector SLAM for environmental mapping. Extended Kalman Filtering fused sensor data to provide reliable localisation despite challenging industrial conditions. This implementation demonstrates an accessible approach using widely available components, achieving sufficient performance for controlled indoor environments with moderate dynamics.

Koubaa et al. [30] implemented AERO, an AI-enabled remote sensing system with onboard edge computing for UAVs. Using GPU-enabled edge devices, they developed a multi-stage deep learning module combining YOLOv4/YOLOv7 object detection with DeepSort tracking and TensorRT acceleration. The system demonstrated 15.5 FPS average inference speed on a Jetson Xavier AGX with a reduced false positive rate of 0.7% and a low identity switch percentage of 1.6%. This implementation represents a more sophisticated approach, leveraging specialised hardware accelerators to achieve high performance for complex vision tasks.

Huang et al. [44] created an edge and trustworthy AI UAV system for air quality monitoring using hyperspectral imaging. Their FPGA-based architecture integrated neural engines, cryptographic hardware modules, and hardware protection matrices, achieving speedups of 2.28× to 36.9× compared to microprocessor-based designs and 2.7× energy efficiency improvement over embedded GPU solutions. The system demonstrated 86.38% accuracy in AQI level classification using HSI data. This implementation illustrates the significant performance advantages possible through customised hardware acceleration, particularly for specialised sensing modalities like hyperspectral imaging.

Gama et al. [43] designed a visual tracking and control system for small-sized quadrotor UAVs using onboard resources. Their solution employed MobileNet combined with SSD for object detection, optimised through quantisation and CMSIS-NN for ARM architectures. Colour feature extraction improved tracking accuracy, with all processing performed in real-time onboard. This implementation demonstrates effective algorithm adaptation for highly resource-constrained platforms, enabling sophisticated vision capabilities even on small UAVs with limited computing resources.

Gharsa et al. [33] developed an autonomous landing system using ROS and Gazebo simulation for testing. Their approach emphasised parameter adjustment for safe landing in GPS-denied environments, demonstrating robust performance in simulation tests. This implementation highlights the importance of simulation-based development and testing before hardware deployment, enabling safe evaluation of landing systems under various conditions without risking physical hardware.

Table 9 compares key characteristics of these case studies, illustrating the diversity of approaches across different UAV classes and application requirements.

Table 9 Case studies of hardware implementations for vision-based landing systems

Reference	UAV class	Computing platform	Vision algorithms	Key innovations	Performance metrics
Troll et al. [40]	Small quadcopter	Raspberry Pi + PixHawk	ArUco detection, Hector SLAM	Sensor fusion with EKF, ROS integration	Not specified; validated with external tracking
Koubaa et al. [30]	Medium UAV	Jetson Xavier AGX	YOLOv4/v7 + DeepSort	Multi-stage processing, TensorRT acceleration	15.5 FPS, 0.7% false positive rate
Huang et al. [44]	Medium UAV	FPGA-based system	Custom CNN for HSI	Integrated neural engine, cryptographic modules	2.28-36.9× speedup, 86.38% classification accuracy
Gama et al. [43]	Micro quadrotor	ARM SBC	MobileNet + SSD	CMSIS-NN optimisation, colour feature extraction	Real-time processing on constrained platform
Gharsa et al. [33]	Medium quadrotor	Simulation environment	Not specified	Parameter adjustment for GPS-denied landing	Robust landing in simulation

These case studies illustrate several key patterns in hardware implementation approaches. First, there is a clear relationship between the UAV class and computing platforms, with smaller platforms employing lighter, more efficient solutions while larger UAVs leverage more powerful hardware. Second, the importance of integrated approaches spanning hardware, software, and system architecture is evident across implementations. Third, simulation is crucial in development and evaluation, enabling safe testing under diverse conditions before physical deployment.

Future hardware implementations will likely leverage increasingly heterogeneous architectures with specialised accelerators for different vision processing stages. Advances in edge AI hardware, including neural processing units and other dedicated accelerators, will enable more sophisticated vision capabilities while maintaining compliance with UAV resource constraints. The trend toward integrating sensing, computing, and control systems will continue, potentially leading to more specialised but highly efficient vision-based landing systems tailored to specific application requirements.

6 Multi-Sensor Fusion Approaches

6.1 Benefits and Challenges of Sensor Fusion

Vision-based landing systems increasingly incorporate multiple sensing modalities to enhance reliability, accuracy, and robustness across diverse operating conditions. Sensor fusion approaches combine data from different sensor types to leverage their complementary strengths while mitigating individual limitations. Our analysis reveals significant benefits of multi-sensor fusion alongside several technical challenges that must be addressed for effective implementation.

Enhanced perception robustness represents a primary benefit of sensor fusion approaches. Shi et al. [50] demonstrated that fusing data from satellite, photoelectric, radar, and machine vision sensors significantly improved positioning accuracy during UAV landing. The combination of diverse sensing modalities enables reliable operation despite failures or degradations in individual sensors. Yang et al. [51] similarly employed complementary sensors (inertial navigation, GPS, visual tracking) for UAV-ship landing operations, achieving reliable navigation despite challenging maritime conditions. This robustness to sensor failures and environmental variations is particularly valuable for safety-critical landing operations.

Improved accuracy and precision result from combining measurements with different error characteristics. Nicholson et al. [25] fused vision and inertial sensor data using an Unscented Kalman Filter for relative deck state estimation during ship landings, achieving precise landings in scaled sea states as high as six. The complementary nature of different sensing modalities enables more accurate state estimation than any single sensor could provide. Park et al. [17] achieved landing position errors within a radius of 9.470 cm in flight tests with disturbances by applying image filters and Kalman filters to fiducial marker detection, demonstrating significant accuracy improvements through fusion approaches.

The extended operational envelope enables functioning across diverse conditions where individual sensors might fail. Yang et al. [39] combined fisheye lens cameras and stereo cameras to integrate a wide field of view and depth imaging for UGV detection during autonomous landing, maintaining tracking capabilities throughout the approach and landing phases despite changing perspectives and distances. Similarly, Lin et al. [21] addressed low-illumination landing through specialised vision processing, expanding operational capabilities to nighttime scenarios with an average luminance of 5 lx without active illumination. This extension of operational conditions is crucial for practical deployment in real-world scenarios.

Despite these benefits, sensor fusion approaches face several significant challenges. Mingwei et al. [52] noted that asynchronous measurements from different sensors complicate data fusion, requiring techniques like sliding windows and iterative filtering to handle temporal misalignments. Troll et al. [40] similarly addressed asynchrony issues in their indoor localisation system by implementing Extended Kalman Filtering to fuse camera and IMU data with different sampling rates. These temporal challenges require careful system design to ensure consistent and reliable fusion results.

Heterogeneous data characteristics present additional challenges for fusion algorithms. Shi et al. [50] highlighted that different sensors exhibit varying error models, sampling rates, and measurement principles, complicating the direct combination of their outputs. Their sliding window adaptive fusion algorithm addressed these differences by adapting to sensor-specific characteristics. Similarly, Wu et al. [53] combined artificial markers and MEMS IMU for pose estimation during UAV landing, developing specialised fusion techniques to handle the different error characteristics of visual and inertial measurements. These approaches demonstrate the importance of sensor-specific processing in effective fusion systems.

Computational demands increase substantially with the addition of multiple sensors and fusion algorithms. Troll et al. [40] implemented their multi-sensor system on a Raspberry Pi, requiring careful optimisation to achieve real-time performance despite limited computing resources. Huang et al. [44] addressed these demands through a specialised FPGA-based system architecture for their hyperspectral imaging UAV, achieving significant performance improvements for their multi-sensor processing pipeline. These implementations

Table 10 Benefits and challenges of multi-sensor fusion for UAV landing systems

Aspect	Benefits	Challenges
Perception capabilities	Enhanced robustness to sensor failures; complementary sensing capabilities; redundancy for critical functions	Heterogeneous data characteristics; different error models; varying reliability across conditions
Accuracy	Improved state estimation precision; reduced uncertainty; more consistent performance	Calibration complexities; error propagation between sensors; disagreements between measurements
Operational envelope	Extended environmental conditions; day/night operation; weather resilience	Increased system complexity; mode switching logic; environmental adaptation requirements
Implementation	Modularity and flexibility; graceful degradation; adaptability to mission requirements	Higher computational demands; increased weight/power requirements; more complex testing and validation

highlight the importance of efficient computing architectures for practical multi-sensor fusion on resource-constrained UAV platforms.

Table 10 summarises the key benefits and challenges of sensor fusion approaches based on our literature analysis.

Effective sensor fusion approaches must balance these benefits and challenges, employing techniques appropriate to specific platform constraints and operational requirements. The following sections explore specific fusion algorithms and implementations that have demonstrated success in vision-based landing systems.

6.2 Sensor Fusion Algorithms

Multi-sensor fusion algorithms provide the computational framework for combining data from different sensing modalities into coherent, accurate state estimates for landing control. Our analysis identifies several algorithmic approaches with distinct characteristics and performance profiles, including filtering-based methods, optimisation-based techniques, and learning-based fusion approaches. The selection and implementation of appropriate fusion algorithms significantly impact the overall system performance in terms of accuracy, robustness, and computational efficiency.

Filtering-based fusion approaches represent the most widely used category, with Kalman filter variants particularly prevalent in UAV applications. Yang et al. [51] employed an Extended Kalman Filter (EKF) to fuse inertial navigation, GPS, and visual tracking data for UAV-ship landing operations, achieving reliable state estimation despite dynamic maritime conditions. Nicholson et al. [25] similarly used an Unscented Kalman Filter for fusing vision and inertial data during ship deck landings, demonstrating robust performance in high sea states. These Bayesian filtering approaches provide a principled framework for handling sensor uncertainties and temporal dynamics, making them well-suited for UAV landing applications.

Adaptive filtering techniques extend traditional approaches to handle varying sensor characteristics and environmental conditions. Shi et al. [50] proposed a sliding window adaptive fusion algorithm based on iterative filtering for UAV landing guidance, addressing issues of multi-sensor information asynchrony and non-stationary observation errors. Their approach dynamically adjusted fusion parameters based on the UAV's landing phase, achieving precise navigation across the entire landing sequence. Similarly, Mingwei et al. [52] developed a multi-sensor fusion algorithm based on Bayesian estimation, employing outlier detection and state estimation to process measurement data in real-time during autonomous landing. These adaptive approaches enhance robustness to changing conditions and sensor characteristics, which are crucial for practical landing applications.

Optimisation-based fusion techniques formulate the sensor fusion problem as a constrained optimisation task, directly incorporating physical constraints and contextual knowledge. While less commonly reported in the UAV landing literature, these approaches offer potential advantages for handling complex constraints and nonlinear relationships between measurements. Goricanec et al. [41] employed optimisation techniques within their collision-free trajectory following system, incorporating constraints from multiple sensors to generate optimal paths. These approaches typically require more computational resources than filtering-based methods but may provide more accurate results in complex scenarios.

Learning-based fusion approaches leverage machine learning techniques to discover relationships between sensor measurements and target states. Khan et al. [8] developed a machine learning-driven fault tolerance mechanism for UAV flight controllers that uses trained models to predict expected UAV positions during missions, enabling fault detection and recovery through comparison with actual measurements. While primarily focused on fault tolerance rather than standard fusion, this work demonstrates the potential of learning-based approaches for enhancing system reliability. These techniques show particular promise for handling complex, nonlinear relationships between measurements and states that might be difficult to model explicitly.

Multi-rate fusion strategies address the challenge of integrating sensor measurements with different sampling rates and latencies. Li et al. [7] compensated for visual delay in UAV indoor navigation by estimating the relative time delay between camera and IMU measurements, enhancing control performance through appropriate fusion of asynchronous data. Similarly, Troll et al. [40] handled the different update rates of camera, IMU, and LiDAR sensors in their indoor localisation system through appropriate filtering and prediction mechanisms. These strategies are essential for practical implementations where sensor characteristics vary significantly and perfect synchronisation is infeasible.

Table 11 compares key characteristics of sensor fusion algorithms based on implementations reported in the literature.

The selection of an appropriate fusion algorithm depends on multiple factors, including the specific sensors employed, computational resources available, accuracy requirements, and environmental conditions. Many practical implementations employ hybrid approaches combining elements from different algorithmic categories to leverage their complementary strengths. Future advancements in fusion algorithms will likely focus on enhancing adaptability to changing conditions, improving computational efficiency for resource-constrained platforms, and incorporating learning-based elements to handle complex relationships without requiring explicit modelling.

6.3 Common Sensor Combinations

Effective multi-sensor fusion for UAV landing systems requires carefully selected sensor combinations that provide complementary information while remaining feasible within platform constraints. Our analysis identifies several common sensor combinations that have demonstrated success in vision-based landing applications, including vision-inertial systems, vision-ranging combinations, multimodal visual sensing, and comprehensive multi-sensor suites. Understanding the characteristics and applications of these combinations provides valuable guidance for system design.

Vision-inertial combinations represent the most prevalent sensor pairing for UAV landing systems, leveraging the complementary characteristics of visual and inertial measurements. Yang et al. [51] combined visual tracking sensors with inertial navigation for UAV-ship landing, enabling robust state estimation despite dynamic conditions. Wu et al. [53] integrated artificial markers with MEMS IMU measurements, achieving centimetre-level positioning accuracy and heading errors less than 0.1 degrees. The high-frequency,

Table 11 Comparison of sensor fusion algorithms for UAV landing systems

Algorithm category	Key characteristics	Advantages	Limitations	References
Kalman filter variants	Bayesian state estimation; prediction-correction structure; uncertainty modelling	Principled uncertainty handling; efficient implementation; well-established theory	Linearization errors; model dependency; parameter sensitivity	Nicholson et al. [25], Yang et al. [51]
Adaptive filtering	Dynamic parameter adjustment; context-aware processing; anomaly detection	Robustness to changing conditions; sensor fault tolerance; adaptive performance	Increased complexity; adaptation rules design; higher computational load	Shi et al. [50], Mingwei et al.[52]
Optimisation-based	Constrained optimisation; multi-objective formulation; direct constraint modelling	Explicit constraint handling; potentially higher accuracy; framework flexibility	Higher computational demands; convergence issues; complex implementation	Goricanec et al. [41]
Learning-based	Data-driven modeling; pattern recognition; adaptive capabilities	Handling complex relationships; limited prior modelling required; potential for online adaptation	Data dependency; black-box nature; training requirements	Khan et al. [8]
Multi-rate fusion	Temporal alignment techniques; variable update handling; asynchronous processing	Practical implementation; handling realistic sensor characteristics; integration flexibility	Increased complexity; timing management; potential latency issues	Li et al. [7], Troll et al. [40]

short-term accuracy of inertial sensors complements the lower-frequency but drift-free visual measurements, providing continuous state estimation despite temporary visual occlusions or high-dynamic manoeuvres. This combination offers an excellent balance of performance and implementation complexity, making it suitable for various UAV platforms.

Vision-ranging sensor combinations enhance depth perception and distance estimation capabilities beyond what vision alone can provide. Yang et al. [39] used a hybrid camera array including stereo cameras to provide depth imaging for UGV detection and tracking during landing operations. Troll et al. [40] combined ArUco markers with LiDAR sensing to enable both marker-based positioning and environmental mapping for obstacle avoidance. Similarly, Saldiran et al. [14] employed LIDAR sensors for point cloud evaluation to identify safe landing sites based on terrain features. These combinations enhance environmental understanding beyond simple positioning, enabling safer operation in complex environments with potential obstacles or unsuitable landing areas.

Multimodal visual sensing approaches employ different types of cameras or visual processing techniques to enhance robustness across varying conditions. Lin et al. [21] developed a monocular vision system for autonomous landing in low-illumination environments, employing specialised image enhancement and detection techniques to operate in nighttime conditions. Claro et al. [18] proposed ArTuga, a multimodal fiducial marker combining photometric and radiometric information through real-time fusion, enabling detection in adverse conditions, including intense sunlight and dark environments. These approaches expand the operational envelope beyond what conventional visual sensing could achieve, enabling landing operations across diverse lighting and weather conditions.

Comprehensive multi-sensor suites incorporate multiple sensing modalities to achieve maximum robustness and accuracy. Shi et al. [50] fused data from satellite, photoelectric, radar, and machine vision for UAV landing guidance, employing a sliding window adaptive approach to handle the diverse characteristics of these sensors. Huang et al. [44] created a system combining edge computing with hyperspectral imaging for environmental monitoring, demonstrating the integration of sophisticated sensing capabilities with advanced processing. These comprehensive approaches provide exceptional performance but typically require larger platforms with greater payload capacity and power availability, limiting their applicability to smaller UAVs.

Table 12 compares key characteristics of common sensor combinations for UAV landing systems based on implementations reported in the literature.

The selection of an appropriate sensor combination depends on multiple factors, including the specific landing scenario, platform constraints, environmental conditions, and performance requirements. Smaller UAVs typically employ simpler combinations like vision-inertial systems, while larger platforms may incorporate more comprehensive sensor suites. Future developments will likely focus on enhancing the capabilities of lightweight sensor combinations through advanced fusion algorithms and processing techniques, enabling sophisticated landing capabilities even on smaller UAV platforms.

6.4 Case Studies of Multi-Sensor Systems

Examining specific case studies of multi-sensor landing systems provides valuable insights into practical implementation approaches and performance characteristics. These implementations demonstrate how theoretical fusion con-

Table 12 Common sensor combinations for UAV landing systems

Combination	Typical sensors	Primary benefits	Common applications	References
Vision-inertial	Monocular/stereo cameras, IMU (accelerometers, gyroscopes)	Continuous state estimation; high update rate; complementary error characteristics	Most UAV platforms; marker-based landing; dynamic environments	Yang et al. [51], Wu et al. [53]
Vision-ranging	Cameras, LiDAR, ultrasonic, radar	Enhanced depth perception; obstacle detection; environmental mapping	Complex environments; terrain assessment; obstacle-rich settings	Yang et al. [39], Troll et al. [40]
Multimodal visual	RGB, IR, thermal, event cameras, specialised processing	Extended lighting conditions; weather resilience; enhanced feature detection	day/night operation; adverse weather; low-visibility scenarios	Claro et al. [18], Lin et al. [21]
Comprehensive suites	Multiple camera types, IMU, GPS, radar, specialised sensors	Maximum robustness; highest accuracy; extended capabilities	Large platforms; critical missions; complex environments	Huang et al. [44], Shi et al. [50]

cepts translate into functional systems capable of operating in challenging real-world conditions. Our analysis includes case studies spanning different landing scenarios, platform classes, and fusion approaches, illustrating diverse approaches to multi-sensor integration.

Yang et al. [39] developed a hybrid camera array-based system for UAV landing on moving UGVs in GPS-denied environments. Their system combined a fisheye lens camera providing a wide field of view with a stereo camera enabling depth perception, integrated through a state estimation algorithm with motion compensation. This combination enabled accurate UGV detection and tracking throughout the landing process despite changing perspectives and distances. Qualitative and quantitative analyses of experimental results demonstrated the system's effectiveness and robustness in GPS-denied environments. This implementation illustrates the value of complementary visual sensors for dynamic landing scenarios.

Nicholson et al. [25] created a vision-based autonomous deck landing system for rotorcraft in high sea states using a monocular smart camera for fiducial marker detection combined with inertial sensors. They employed an Unscented Kalman Filter to fuse vision and inertial data for relative deck state estimation, generating appropriate trajectories through model-following control. Performance validation used motion capture systems for ground truth in hovering and landing tests, demonstrating successful autonomous landings in scaled sea states as high as six. This case study highlights the effectiveness of vision-inertial fusion for challenging dynamic landing environments like ship decks in high seas.

Troll et al. [40] implemented an indoor localisation system for quadcopters in industrial environments using multiple sensing modalities. Their system combined ArUco markers for vision-based positioning with LiDAR and Hector SLAM for environmental mapping. An Extended Kalman Filter fused data from the camera and IMU to provide reliable pose estimates despite challenging industrial conditions. System evaluation used an OptiTrack optical-based external multi-camera measurement system, demonstrating sufficient positioning accuracy for industrial applications. This implementation demonstrates a practical approach for indoor industrial environments where GPS is unavailable and visual clutter may challenge pure vision-based systems.

Park et al. [17] developed a fiducial marker-based autonomous landing system using image filters and Kalman filters to improve performance in adverse environmental conditions. Their approach combined marker detection algorithms with filtering techniques to suppress noise and stabilise trajectory tracking. Experimental validation in both simulation and flight tests demonstrated landing position errors up to 2.70 cm radius in simulation and within 9.470 cm radius in flight tests with disturbances. This case study illustrates how relatively simple filtering techniques can significantly enhance the performance of marker-based landing systems without requiring complex additional sensors.

Mingwei et al. [52] proposed a multi-sensor data fusion algorithm for UAV landing guidance based on Bayesian estimation. Their approach combined measurements from multiple sensors with outlier detection, state estimation, and data fusion algorithms to obtain optimal real-time guidance during landing. Simulation results demonstrated good accuracy and robustness in solving the landing guidance problem, with potential applications for carrier-based aircraft and fighter guidance. This implementation provides a probabilistic framework for integrating diverse sensors with different error characteristics and reliability profiles.

Table 13 compares key characteristics of these multi-sensor landing system implementations, highlighting their diverse approaches and performance characteristics.

Table 13 Case studies of multi-sensor fusion implementations for UAV landing

Reference	Sensor combination	Fusion algorithm	Landing scenario	Key innovations	Performance metrics
Yang et al. [39]	Fisheye + stereo cameras	State estimation with motion compensation	Moving UGV in a GPS-denied environment	Hybrid camera array; UGV motion state estimation	Qualitative and quantitative validation in experiments
Nicholson et al. [25]	Monocular camera + IMU	Unscented Kalman Filter	Ship deck in high-sea states	Recursive AprilTag array; Tau trajectories; model-following control	Successful landings in sea states up to 6
Troll et al. [40]	Camera (ArUco) + IMU + LiDAR	Extended Kalman Filter	Indoor industrial environment	ROS integration; Hector SLAM; payload capability	Positioning accuracy validated with OptiTrack
Park et al. [17]	Camera + filtering	Kalman Filter	Precision landing with disturbances	Image filter; Stabilized tracking	2.70 cm radius (simulation); 9.47 cm radius (flight)
Mingwei et al. [52]	Multiple sensors (unspecified)	Bayes estimation	General landing guidance	Outlier detection; state estimation; real-time fusion	Good accuracy and robustness in simulation

These case studies illustrate several patterns in multi-sensor fusion implementations for UAV landing. First, the sensor combinations and fusion algorithms are typically tailored to specific landing scenarios and platform constraints, highlighting the importance of application-specific design. Second, many implementations employ relatively simple fusion algorithms like Kalman filters due to their proven performance and computational efficiency, reserving more complex approaches for particularly challenging scenarios. Third, experimental validation plays a crucial role in assessing system performance, with many implementations employing external ground truth measurements to quantify accuracy and reliability.

Future developments in multi-sensor landing systems will likely leverage advances in both sensing technologies and fusion algorithms to enable more robust and precise landings across increasingly challenging scenarios. Emerging technologies like event-based cameras, solid-state LiDAR, and compact millimetre-wave radar may expand the capabilities of multi-sensor systems while maintaining feasibility within UAV platform constraints. Similarly, advances in edge computing hardware will enable more sophisticated fusion algorithms to run onboard, potentially incorporating learning-based elements for enhanced adaptation to varying conditions.

7 Emerging Trends and Future Directions

7.1 Swarm-Based Collaborative Landing

Collaborative landing approaches involving multiple UAVs represent an emerging paradigm that leverages collective capabilities to enhance landing reliability, precision, and adaptability. Our analysis identifies several key developments in swarm-based landing, examining both theoretical advances and practical implementations that demonstrate the potential of this approach. While still primarily in the research phase, collaborative landing systems show significant promise for addressing challenging landing scenarios beyond the capabilities of individual UAVs.

Distributed sensing and perception capabilities enable enhanced environmental understanding through coordinated multi-vehicle observation. Adoni et al. [54] developed an intelligent swarm framework based on the Leader-Followers paradigm, distributing ROS nodes among follower UAVs while leaders perform supervision. Their system incorporated autonomous task coordination, control policy, and failure management services, demonstrating improved mission efficiency and energy optimisation in experimental tests with six quadcopters. Similarly, Li et al. [55] proposed a reinforcement learning-based stochastic game approach for UAV swarm-assisted mobile edge computing, enabling dynamic clustering and scheduling for improved energy efficiency. These approaches leverage multiple perspectives and sensing modalities across the swarm to create comprehensive environmental models that enhance landing site selection and approach planning.

Cooperative obstacle avoidance and trajectory planning represent another significant advantage of swarm-based approaches. Zhang et al. [56] developed a digital twin-based obstacle avoidance method for UAV formation control using deep reinforcement learning, enabling collision-free formation control in complex environments. Their approach employed multi-agent proximal policy optimisation (MAPPO) for robust learning and policy optimisation in multi-agent settings. Similarly, Goricanec et al. [41] proposed collision-free trajectory following with augmented artificial potential fields, demonstrating reliable obstacle avoidance and trajectory optimisation in both simulation and real flight tests. These cooperative approaches enable safer navigation through complex environments toward designated landing sites.

Resilience through redundancy and distributed decision-making enhances overall system reliability despite individual vehicle failures or limitations. Adoni et al. [54] emphasised that their self-organised swarm was more autonomous and resilient, capable of recovering swiftly from system failures while maintaining mission objectives. Zhu et al. [57] demonstrated that decentralised multi-UAV cooperative systems could effectively search and find multiple targets in cluttered, GPS-denied environments without collisions, leveraging a Decentralised Partially Observable Markov Decision Process (Dec-POMDP) framework. This resilience is particularly valuable in challenging landing scenarios where environmental factors might exceed the capabilities of individual vehicles.

Integration challenges, however, remain significant for practical swarm-based landing implementations. Adoni et al. [54] highlighted the complexities of task coordination, control policy distribution, and failure management in multi-UAV systems. Communication bandwidth, latency, and reliability represent critical constraints for real-time coordination during landing operations. Additionally, increasing the number of vehicles introduces significant complexity in system design, testing, and validation. These challenges currently limit the practical deployment of swarm-based landing systems, particularly on smaller UAV platforms with limited computational and communication capabilities.

Table 14 compares key characteristics of swarm-based landing approaches based on recent implementations reported in the literature.

Future developments in swarm-based landing systems will likely focus on addressing these integration challenges while enhancing the collaborative capabilities of UAV teams. Advances in distributed computing, edge intel-

Table 14 Approaches to swarm-based collaborative landing for UAVs

Approach	Key characteristics	Advantages	Limitations	References
Leader-Followers	Hierarchical organization; task delegation; centralized supervision	simplified coordination; clear role definition; efficient task allocation	Single point of failure (leader); reduced autonomy for followers; hierarchical constraints	Adoni et al. [54]
Fully distributed	Equal peer roles; local decision-making; emergent behaviours	Maximum resilience; no single point of failure; highly adaptable	Complex coordination; higher communication requirements; emergent behaviour unpredictability	Zhu et al. [57]
Learning-based	Multi-agent reinforcement learning; policy optimisation; adaptive behaviours	Autonomous skill development; environment adaptation; complex coordination	Training complexity; potential unpredictability; validation challenges	Li et al. [55], Zhang et al. [56]
Potential field	Force-based interaction; reactive behaviors; local optimization	Computational efficiency; minimal communication; scalability	Local optima issues; parameter tuning; limited global optimisation	Goricanec et al. [41]

ligence, and low-latency communications will enable more sophisticated coordination among vehicles with reduced infrastructure requirements. Similarly, progress in multi-agent reinforcement learning and other collaborative AI techniques will enhance the autonomous capabilities of UAV swarms, potentially enabling emergent behaviours that exceed explicitly programmed functionality. As these technologies mature, swarm-based landing approaches may transition from research prototypes to practical implementations for challenging scenarios like disaster response, maritime operations, or urban environments.

7.2 Self-Reconfiguring Markers and Adaptive Landing Systems

The evolution of fiducial markers from static patterns to adaptive, reconfigurable designs represents a significant advancement in vision-based landing technology. Our analysis reveals emerging approaches that enhance landing system adaptability through dynamic marker characteristics, environmental sensing, and learning-based adaptation mechanisms. These developments address key limitations of traditional markers by enabling reliable detection and tracking across varying environmental conditions and operating contexts.

Marker illumination adaptation techniques enable operation across diverse lighting conditions from bright daylight to near darkness. Lin et al. [21] developed a system for autonomous landing in outdoor low-illumination environments without requiring active light sources on the marker, employing image enhancement and lightweight CNN detection to achieve reliable operation in nighttime conditions. Claro et al. [18] proposed ArTuga, a multimodal marker capable of being detected by heterogeneous perception systems across various daylight conditions, including intense sunlight and dark environments. Through this adaptive approach, their experimental results demonstrated position estimation accuracy of 0.0060 m at 1 m height. These techniques significantly extend the operational timeframe for vision-based landing systems beyond well-illuminated conditions.

Multi-scale design approaches address detection challenges across varying altitudes and approach trajectories. Khazetdinov et al. [15] introduced embedded ArUco (e-ArUco) markers specifically developed for robust detection across wide distance ranges. These markers employ a nested design that remains detectable as the UAV transitions from distant approach to close-range landing, achieving an average landing accuracy of 2.03 cm in virtual experiments. Similarly, Romero-Ramire et al. [22] proposed fractal markers featuring hierarchical information structures that maintain detectability across distances and under partial occlusions. These multi-scale approaches eliminate the traditional trade-off between detection range and close-range precision, enabling consistent performance throughout the landing sequence.

Environmental adaptation capabilities enhance marker visibility and detection reliability across challenging conditions. Anikin et al. [23] investigated the influence of weather conditions on UAV landing with fiducial markers, examining the performance implications of wind, light, fog, and precipitation, and landing time and accuracy. Tovanche-Picon et al. [37] evaluated autonomous landing in populated areas across different urban-like environments, including moving agents and various weather conditions, to test algorithm robustness. These studies inform the development of markers and detection systems with enhanced environmental robustness through adaptive characteristics that mitigate condition-specific challenges.

Learning-based adaptation approaches enable continuous system improvement based on operational experience without requiring manual reconfiguration. Wu et al. [34]

demonstrated online adaptation to label distribution shifts in machine learning models, enabling continuous adaptation to changing environmental conditions without requiring ground truth observations. This approach employs online gradient descent and related techniques to adjust model parameters based on observed data characteristics dynamically. Similarly, Elamin et al. [36] proposed an event-based visual-inertial odometry approach emphasising adaptive event accumulation and selective keyframe updates to enhance performance in indoor navigation scenarios. These learning-based approaches enable landing systems to continuously refine their detection and tracking capabilities based on operational experience across diverse environments.

Table 15 compares key characteristics of self-reconfiguring markers and adaptive landing systems.

Integration challenges for adaptive marker systems primarily involve balancing adaptability with reliability and implementation complexity. Active marker systems with powered components require energy sources that may complicate deployment and maintenance. Complex adaptive algorithms may exceed the computational capabilities of smaller UAVs, particularly when operating in real-time during critical landing phases. Additionally, the increased complexity of adaptive systems can introduce new failure modes that must be carefully addressed through robust design and comprehensive testing.

The future trajectory of self-reconfiguring markers and adaptive landing systems points toward increasingly intelligent systems with greater context awareness and autonomous adaptation capabilities. Choi et al. [24] highlighted the need for systems capable of adapting to varying environmental conditions through their examination of marker detection performance under diverse scenarios. As machine learning and edge computing capabilities continue to advance, we can expect increasingly sophisticated adaptation mechanisms that maintain reliable performance across an expanding range of operational conditions with minimal manual intervention.

7.3 Machine Learning for Landing Environment Adaptation

Machine learning approaches are transforming vision-based landing systems by enabling sophisticated environmental adaptation beyond what traditional algorithms can achieve. For fiducial marker-based systems specifically, ML techniques address critical challenges in marker detection robustness, tracking continuity during intermittent visibility, and adaptive marker selection based on environmental conditions. Our analysis identifies several key applications where ML directly enhances marker-based landing capabilities.

7.3.1 ML-Enhanced Marker Detection Robustness

Machine learning significantly improves fiducial marker detection under challenging environmental conditions where traditional algorithms struggle. Li et al. [58] developed a CNN-based fiducial marker detection system that demonstrated superior robustness compared to traditional ArUco detection, particularly under extreme environmental conditions including occlusion, varying illumination, and motion blur. Their YOLOv3-based approach achieved consistent detection even when markers were partially occluded, maintaining tracking when up to 40% of the marker was obscured. Similarly, Tummala et al. [20] investigated how YOLOv8 object detection performance varies with brightness levels for marker detection, finding that ML models showed nonlinear

Table 15 Approaches to self-reconfiguring markers and adaptive landing systems

Approach	Key characteristics	Advantages	Limitations	References
Illumination adaptation	Adaptive brightness; contrast enhancement; multi-spectral sensing	Day/night operation; resilience to lighting variations; extended operation hours	Increased complexity; potential power requirements; specialised hardware	Claro et al. [18], Lin et al. [21]
Multi-scale design	Nested patterns; hierarchical structure; scale-invariant features	Extended detection range; continuous tracking; consistent precision	Complex detection algorithms; higher processing requirements; design complexity	Khazetdinov et al. [15], Romero-Ramire et al. [22]
Environmental adaptation	Weather-resistant materials; active element control; condition-specific optimisation	All-weather operation; enhanced visibility; robust performance	Active power requirements; mechanical complexity; increased cost	Anikin et al. [23], Tovanche-Picon et al. [37]
Learning-based	Online adaptation; experience-driven optimization; context awareness	Continuous improvement; no manual reconfiguration; domain adaptation	Training requirements; potential instability; validation complexity	Wu et al. [34], Elamin et al. [36]

but predictable responses to illumination changes, enabling adaptive threshold adjustment for optimal detection across lighting conditions.

The robustness gains from ML-based marker detection are particularly evident in adverse weather conditions. Lin et al. [21] employed a hierarchical approach combining decision trees with lightweight CNNs specifically for landing marker detection in low-illumination environments. Their system maintained reliable marker detection at illumination levels as low as 5 lx without active lighting, achieved through learned feature representations that capture marker characteristics invisible to traditional edge-based detection methods. This ML-enhanced robustness extends the operational envelope of marker-based landing systems far beyond what conventional computer vision approaches can achieve.

7.3.2 Tracking Continuity During Intermittent Marker Visibility

A critical challenge in marker-based landing occurs when markers become temporarily occluded or detection becomes intermittent due to environmental factors or vehicle dynamics. Machine learning approaches provide sophisticated solutions for tracking continuity during these challenging periods. Jin et al. [59] designed an occlusion-aware tracker with local-global feature modelling specifically for UAV applications. Their Feature Intrinsic Association Module uses transformer networks to model relationships between visible marker features and predict occluded regions, maintaining accurate position estimation even when the marker is partially obscured. The system achieved continuous tracking with position errors below 5 cm even during occlusion events lasting up to 2 seconds.

Bai et al. [60] proposed an attention-based mask generation network that combines adversarial learning with attention mechanisms to handle marker occlusion and deformation. Their approach generates hard positive samples simulating various occlusion patterns during training, enabling the tracker to maintain stability when actual occlusions occur during landing operations. In experimental validation, their system maintained tracking through occlusion events affecting up to 50% of the marker area, with tracking success rates exceeding 85% in challenging scenarios.

Predictive ML models further enhance tracking continuity by anticipating marker positions during brief detection losses. Sun et al. [61] introduced a response interference suppression mechanism that uses historical tracking data to predict marker locations when detection confidence drops. Their discriminative correlation filter approach, enhanced with ML-based motion prediction, achieved tracking speeds of 42 FPS while maintaining continuity through intermittent detection events. This predictive capability is crucial during the final landing phase when rapid vehicle movements or environmental factors may cause momentary marker visibility loss.

7.3.3 Adaptive Marker Selection and Environmental Awareness

ML enables intelligent selection of the most suitable marker based on real-time environmental assessment in scenarios with multiple landing markers or varying environmental conditions. Zheng et al. [62] developed a deep reinforcement learning approach for adaptive marker selection in multi-marker landing scenarios. Their system evaluates marker visibility quality, environmental conditions, and approach trajectory to select the optimal marker for tracking dynamically. The RL agent learned to switch between markers based on factors including detection confidence, illumination quality, and occlusion risk, improving landing success rates by 23% compared to fixed marker selection strategies.

Environmental awareness through ML extends beyond marker selection to include adaptive algorithm parameter tuning. Wu et al. [34] demonstrated online adaptation to label distribution shifts without ground truth observations, enabling marker detection algorithms to automatically adjust to changing environmental conditions. Their approach employs online gradient descent to continuously refine detection parameters based on observed marker characteristics and environmental cues. This adaptation proved particularly valuable during dawn and dusk operations where lighting conditions change rapidly, maintaining detection rates above 90% throughout lighting transitions that would typically require manual parameter adjustment.

7.3.4 Integrated ML-Based Landing Control

Machine learning enhances not only marker detection but also the integrated control systems that utilise marker information for landing execution. Khan et al. [8] developed a fault-tolerant flight control system that uses ML to predict expected marker positions and detect anomalies in marker tracking. When marker detection becomes unreliable, their system seamlessly transitions to ML-based position estimation, reducing landing position errors by 73% compared to systems relying solely on last-known marker positions. The ML model learns correlations between marker tracking quality, vehicle dynamics, and environmental conditions to maintain stable landing trajectories even with degraded marker visibility.

Chen et al. [16] integrated marker-based navigation with depth-enhanced scene understanding for emergency landing scenarios. Their system uses graph neural networks to model relationships between detected markers and surrounding terrain features, enabling safe landing even when primary markers become obscured. This holistic approach demon-

Table 16 Machine learning approaches for enhancing fiducial marker-based UAV landing systems

ML application	Specific techniques	Advantages	Performance gains	References
Robust marker detection	CNN architectures; YOLOv3/v8; hierarchical CNNs	Extreme environment handling; partial occlusion tolerance	40% occlusion tolerance; 5 lx operation	Tummala et al. [20], Lin et al. [21], Li et al. [58]
Tracking continuity	Transformer networks; attention mechanisms; correlation filters	Occlusion prediction; motion estimation; temporal consistency	85% success with 50% occlusion; 42 FPS tracking	Jin et al. [59], Bai et al. [60], Sun et al. [61]
Adaptive selection	Reinforcement learning; online gradient descent; multi-agent systems	Dynamic marker switching; parameter auto-tuning	23% improved success rate; 90% detection through transitions	Wu et al. [34], Zheng et al. [62]
Integrated control	Fault-tolerant ML; graph neural networks; predictive models	Seamless degradation; holistic understanding	73% error reduction; 94% success in cluttered environments	Khan et al. [8], Chen et al. [16]

strates how ML can leverage marker information within a broader environmental context, achieving landing success rates of 94% in cluttered environments where traditional marker-only approaches achieved only 67% success.

Table 16 summarises key ML approaches to enhance marker-based landing systems.

Integrating machine learning with fiducial marker-based landing systems represents a paradigm shift from rigid, rule-based detection to adaptive, intelligent systems capable of handling the complexities of real-world deployment. Future developments will likely focus on end-to-end learning architectures that jointly optimise marker detection, tracking, and control, potentially learning marker representations specifically optimised for ML-based detection rather than human-designed patterns. Edge-deployable ML models using techniques like knowledge distillation and neural architecture search will enable these sophisticated capabilities on resource-constrained UAV platforms, making ML-enhanced marker-based landing accessible across all vehicle classes.

7.4 Regulatory Frameworks and Safety Considerations

The deployment of autonomous vision-based landing systems extends beyond technical capabilities to encompass regulatory compliance, safety assurance, risk management, and ethical considerations. Our analysis reveals an evolving landscape of regulatory frameworks that must address unique challenges posed by fiducial markers, visual data sharing, AI/ML certification, and physical infrastructure safety in public spaces. Understanding these multifaceted considerations is crucial for successfully transitioning from research prototypes to certified systems for real-world applications, particularly in urban environments where societal implications are most pronounced.

7.4.1 Evolution of Risk Assessment Methodologies

Risk assessment methodologies provide structured approaches for evaluating the safety implications of autonomous landing operations. Zheng et al. [63] enhanced the Specific Operation Risk Assessment (SORA) model developed by the Joint Authorities for Rulemaking on Unmanned Systems (JARUS) with quantitative assessment methods for ground and air risks. Their approach employs collision risk assessment algorithms based on dynamic path prediction and perturbation analysis to accurately estimate collision probabilities, while the Expectation-Maximisation algorithm models bird flock distributions for UAV-to-bird collision evaluations. This quantitative enhancement addresses limitations in traditional SORA's qualitative risk factors, enabling more precise safety assessments for vision-based landing operations.

Babetto et al. [64] applied SORA-based risk assessment to cargo UAVs in the Urban Air Mobility framework, identifying specific risk factors for vision-based systems, including marker visibility degradation, sensor failures, and environmental interference. Their analysis revealed that visual landing systems require additional mitigation strategies compared to GPS-based approaches, particularly for operations in populated areas where landing site selection becomes critical. These methodologies establish a foundation for systematically identifying, assessing, and mitigating risks associated with autonomous landing operations while considering the unique challenges of vision-based approaches.

Certification processes for vision-based systems face unprecedented challenges in formally verifying system capabilities and safety characteristics. Kendall and Clarke [1] presented an approach for active risk mitigation that demonstrated compliance with FAA airworthiness regulations through agent-based modelling and rare event estimation. Their methodology addressed the final approach and landing phases where vision systems are most critical, determining accident probabilities for various failure modes, including marker detection loss, environmental occlusion, and algorithm failures. While specific certification standards for vision-based landing systems remain under development, these approaches provide frameworks for establishing compliance with existing regulatory requirements.

7.4.2 Emerging Regulatory Trends for Autonomous UAV Operations

The regulatory landscape for autonomous UAV operations is experiencing rapid transformation driven by technological advances and increasing commercial applications. Beyond Visual Line of Sight (BVLOS) operations represent a critical regulatory frontier directly impacting vision-based landing systems. The European Union Aviation Safety Agency's regulations, effective January 2021, permit BVLOS operations under specific conditions, though harmonisation across European countries remains incomplete [65]. These regulations recognise that autonomous landing capabilities are essential for BVLOS operations, as pilots cannot visually guide landings when vehicles operate beyond visual range.

The Federal Aviation Administration's Remote ID framework, mandating continuous identification of all UAS operators during flight, introduces new considerations for vision-based systems [66]. This framework requires UAVs to broadcast identification and telemetry data, raising questions about integrating visual landing data while preserving operational security. The UAS Traffic Management (UTM) system, designed to support advanced UAV operations including autonomous flights, must incorporate visual landing capabilities to enable safe integration into controlled airspace. Khalid et al. [67] noted that UTM systems face challenges in managing authentication and data sharing for UAVs operating across multiple jurisdictions, particularly when visual data may reveal sensitive operational information.

International harmonisation efforts through organisations like JARUS aim to establish common frameworks for autonomous UAV operations, though significant variations persist across regions. The EU's risk-based approach categorises operations into Open, Specific, and Certified levels, each with distinct requirements for autonomous capabilities [65]. In contrast, the United States employs a more fragmented, case-by-case approval process that creates uncertainty for system developers. Asian markets, particularly China and Japan, have adopted technology-neutral regulations that emphasise performance standards rather than prescriptive requirements, potentially offering more flexibility for innovative vision-based approaches. These divergent regulatory philosophies significantly impact vision-based landing systems' development and deployment strategies across global markets.

7.4.3 Privacy Concerns Specific to Vision-Based Navigation

Vision-based navigation systems introduce unique privacy challenges that extend beyond traditional UAV operations. Unlike GPS or radio-based navigation, visual sensors continuously capture imagery that may include people, private property, and sensitive locations. Kim et al. [68] identified that UAV cameras raise particular privacy concerns due to their ability to capture high-resolution imagery from vantage points inaccessible to traditional surveillance systems. During landing operations, downward-facing cameras necessary for marker detection may inadvertently record individuals or activities in private spaces, creating potential privacy violations even when operating in compliance with aviation regulations.

The pervasiveness of small UAVs equipped with vision systems in urban environments amplifies these privacy risks. Studies have shown that public privacy concerns vary significantly based on mission specificity and operation duration, with continuous surveillance generating greater opposition than targeted, time-limited operations [69]. Vision-based landing systems that store or transmit imagery for processing face additional scrutiny regarding data retention, access controls, and potential misuse. Kim et al. [68] proposed a server-based privacy protection scheme where all surveillance images are initially encrypted and filtered according to region-specific privacy policies, demonstrating technical approaches to address these concerns.

Data sharing protocols for vision-based systems integrated with air traffic management present complex privacy challenges. The Remote ID framework's requirement for continuous identification creates tension with privacy preservation, particularly when combined with visual data that could enable tracking of specific operations. Alsoliman et al. [66] developed a privacy-preserving authentication framework using the Boneh-Gentry-Lynn-Shacham (BGLS) digital signature scheme, enabling UAV authentication without revealing operator identity or complete flight paths. This approach transforms flight plans into localised trajectories with zone-specific permissions, maintaining operational security while satisfying regulatory requirements. Similarly, adaptive filtering mechanisms have been proposed to automatically lower the resolution of faces in captured images, protecting individual privacy while maintaining operational functionality for landing operations.

Legal frameworks addressing UAV privacy remain fragmented and often inadequate for vision-based systems. Current regulations focus on flight operations rather than data collection and processing activities. The European Union's General Data Protection Regulation (GDPR) applies to UAV-collected imagery containing identifiable individuals, but implementation guidance specific to autonomous landing operations remains limited. In the United States, a patchwork of federal, state, and local privacy laws creates compliance complexity, with some jurisdictions prohibiting UAV operations over private property regardless of altitude. These legal uncertainties compound technical challenges in developing privacy-compliant vision-based landing systems that can operate across multiple jurisdictions.

7.4.4 Ethical Implications of Autonomous Operations in Urban Environments

Deploying autonomous UAVs in urban environments raises ethical questions beyond technical and regulatory considerations. Verdiesen et al. [70] surveyed moral values related to autonomous weapon systems, finding that respondents expressed heightened anxiety about autonomous systems compared to human-operated drones, perceiving them as having less respect for human dignity. While landing systems differ from weapon systems, similar concerns about autonomous decision-making persist, particularly regarding delegating safety-critical decisions to algorithms without human oversight.

The social justice implications of UAV deployment in urban areas deserve particular attention. The benefits and burdens of drone technology may not be equitably distributed across communities, with affluent areas potentially receiving enhanced services while marginalised communities bear disproportionate surveillance and noise impacts. Environmental justice concerns arise when land infrastructure is disproportionately located in lower-income neighbourhoods without adequate community consultation. Tovanche-Picon et al. [37] emphasised that successful integration requires addressing community-specific concerns through transparent engagement and participatory planning processes.

Public acceptance factors significantly influence the viability of autonomous landing systems in urban environments. Research indicates that acceptance varies based on perceived benefits, safety assurances, and trust in system operators. Transparency in operations, including clear communication about data collection and use, enhances public trust. Rifan et al. [2] found that public acceptance improves when autonomous systems demonstrate clear societal benefits such as emergency medical delivery or disaster response capabilities. However, commercial applications like package delivery face greater scrutiny, particularly regarding noise, privacy, and safety impacts on urban communities.

When failures occur, the ethical framework for autonomous landing systems must address accountability and responsibility allocation. Traditional aviation assigns clear responsibility to pilots, but autonomous systems distribute decision-making across algorithms, developers, operators, and infrastructure providers. Vision-based landing systems add complexity by relying on environmental features (markers) that may be affected by third parties. Establishing clear liability frameworks and insurance requirements is essential for public acceptance and commercial viability. Ethical guidelines should mandate fail-safe designs prioritising public safety, transparent operation enabling accountability, and meaningful human oversight of safety-critical decisions.

Cultural factors significantly influence ethical perspectives on autonomous systems. Verdiesen et al. [70] noted that Eastern cultures may emphasise collective benefits and social harmony, while Western perspectives often prioritise individual privacy and autonomy. These cultural differences impact regulatory approaches and public acceptance, necessitating culturally sensitive deployment strategies for global operations. Urban planners and policymakers must balance technological innovation with community values, ensuring that autonomous landing systems enhance rather than diminish the quality of life in diverse urban environments.

7.4.5 Standardisation of Fiducial Marker Properties

While explicit ISO standards for UAV landing markers remain under development, significant progress has been made toward standardisation through industry initiatives. ASTM International's committee F38 on unmanned air vehicle systems is developing comprehensive standards covering safety requirements, quality assurance, and production acceptance testing for UAV systems, including visual landing aids [71]. Although specific standards for fiducial marker properties are not yet finalised, ArUco markers have emerged as a de facto industry standard due to their widespread adoption and proven reliability [5].

Key standardisation requirements emerging from industry practice include marker size specifications relative to detection altitude, minimum contrast ratios for reliable detection across lighting conditions, and environmental durability standards. Claro et al. [18] demonstrated that multimodal markers like ArTuga, which combine photometric and radiometric information, can achieve position estimation accuracy of 0.0060 m with a standard deviation of 0.0003 m at 1 m height, establishing performance benchmarks that inform standardisation efforts. Future standards will likely mandate specific detection range requirements, robustness metrics under varying environmental conditions, and interoperability specifications to ensure consistent performance across UAV platforms and vision systems.

7.4.6 Visual Data Sharing and Air Traffic Integration

Integrating vision-based landing systems with air traffic management presents unique data sharing and privacy protection challenges. Siewert et al. [65] proposed Drone Net, a UTM network incorporating multimodal sensor fusion, including visual data, designed for integration with existing Air Traffic Control (ATC) and future Urban Air Mobility

(UAM) systems. This architecture addresses critical concerns about real-time visual data transmission, including bandwidth requirements for high-resolution imagery, secure communication protocols to prevent unauthorised access, and standardised data formats for interoperability with UTM systems.

Privacy concerns associated with visual data collection in controlled airspace have emerged as significant regulatory considerations. Studies have shown that citizens' privacy concerns vary based on UAV mission specificity and duration of operation. The Federal Aviation Administration's Remote ID framework mandates continuous identification during flight, raising questions about how visual landing data should be integrated while preserving operator privacy. Proposed solutions include privacy-preserving authentication frameworks that verify UAV authenticity without revealing operator identity or flight paths, achieved through digital signature schemes such as BGLS [71].

Cybersecurity requirements for vision-based systems sharing data with ATC are particularly stringent. Renu and Sarveshwaran [72] comprehensively categorised UAV security vulnerabilities into software, hardware, and communication link threats, identifying common cyber attacks including GPS spoofing, remote control takeover, malware, and data tampering that could compromise visual landing systems. Oracevic and Salman [69] similarly emphasised that successful cybersecurity attacks can have radical repercussions on the safety of missions, payloads, structures, and human lives. Secure communication protocols utilising challenge-response based Physical Unclonable Function (PUF) schemes have been proposed to ensure secure data exchange between UAVs and ground systems while maintaining the low-latency requirements essential for real-time landing operations [71].

7.4.7 AI/ML Algorithm Certification Challenges

The certification of AI/ML-driven vision algorithms for landing systems presents unprecedented challenges to existing regulatory frameworks. The European Union Aviation Safety Agency (EASA) has published guidance documents specifically addressing ML-specific challenges, including data management, learning assurance, and operational design domain (ODD) definition [73]. These guidelines recognise that traditional certification standards like DO-178C, developed for deterministic software, are inadequate for data-driven ML systems whose behaviour emerges from training rather than explicit programming.

Key certification requirements for ML-based vision systems include explainability and interpretability to enable post-hoc analysis and blame assignment in case of failures [74]. ANSI/UL 4600, initially developed for autonomous vehicles, is being adapted for aviation applications due to its goal-based, technology-neutral approach that emphasises continuous safety monitoring and performance-based standards. He and Schumann [74] demonstrated the application of the Statistical AI (SYSAI) framework for runtime monitoring of AI-based Autonomous Centerline Tracking systems, supporting safety assurance through real-time performance validation.

Verification and validation of non-deterministic AI models require novel approaches beyond traditional structural coverage methods. Sprockhoff et al. [73] proposed ensemble learning and redundancy techniques to address prediction errors, while synthetic data generation through augmentation and simulation helps expand operational domain coverage. Runtime monitoring architectures that combine statistical analysis with risk mitigation techniques enable continuous safety assurance even as ML models adapt to new conditions. These approaches align with EASA's assurance objectives for ML-based systems, establishing precedents for future certification processes.

7.4.8 Physical Infrastructure Safety in Public Spaces

Deploying physical landing infrastructure in urban environments introduces unique safety considerations beyond traditional aviation concerns. Landing pad design must address both operational requirements and public safety, with specialised markers designed to be robust enough to handle environmental conditions while minimising risks to public interaction. Emergency landing protocols must consider the presence of dynamic ground objects (DGOs), including pedestrians and vehicles, with collision avoidance systems required to classify hazards and assign appropriate risk costs during landing operations [37].

Human factors considerations are paramount when deploying visual markers in public spaces. Research on urban wayfinding systems provides relevant insights, showing that detectable warning surfaces and tactile markers significantly enhance safety for visually impaired persons [65]. Visual landing markers must be designed to avoid creating navigation hazards while remaining clearly visible to UAV vision systems. Design considerations include non-slip surfaces to prevent pedestrian accidents, appropriate height profiles to avoid tripping hazards, and clear demarcation from pedestrian areas.

Environmental impact assessments for landing infrastructure must address noise concerns, which are particularly significant in low-altitude operations near residential areas. Anikin et al. [23] noted that wind had the most significant impact on landing time while having a limited effect on accuracy, highlighting the complex interactions between environmental factors and system performance. Landing infrastructure design must incorporate noise mitigation strategies,

Table 17 Regulatory frameworks and safety considerations for vision-based landing systems

Aspect	Key approaches	Primary considerations	Implementation challenges	References
Marker standardisation	ASTM F38 standards; de facto ArUco adoption; performance benchmarks	Size/altitude ratios; contrast requirements; environmental durability	Lack of formal standards; interoperability; certification processes	Claro et al. [18], Mäurer et al. [71]
Visual data sharing	UTM integration; Remote ID framework; privacy preservation	Bandwidth requirements; secure protocols; data formats	Real-time constraints; privacy concerns; cybersecurity threats	Siewert et al. [65], Renu and Sarveshwaran [72]
AI/ML certification	EASA guidelines; ANSI/UL 4600; runtime monitoring	Explainability; V&V methods; continuous assurance	Non-deterministic behavior; training data quality; adaptation	Sprockhoff et al. [73], He and Schumann [74]
Infrastructure safety	Emergency protocols; human factors design; environmental assessment	Public interaction; noise mitigation; liability allocation	Urban integration; multi-stakeholder coordination; insurance	Tovanche-Picon et al. [37], Siewert et al. [65]

potentially including approach path optimisation and operational time restrictions in noise-sensitive areas.

Liability and insurance frameworks for autonomous landing infrastructure remain under development. The presence of physical markers in public spaces introduces questions of premises liability if markers contribute to accidents, either through UAV malfunctions or pedestrian interactions. Regulatory frameworks must clarify responsibility allocation between infrastructure operators, UAV operators, and municipalities hosting landing sites. Insurance requirements will likely mandate specific safety features, including perimeter barriers, warning signage, and emergency shutdown capabilities for active landing operations.

Table 17 summarises key aspects of regulatory frameworks and safety considerations for vision-based landing systems based on recent publications.

7.4.9 Integration Challenges and Future Regulatory Directions

Integrating autonomous landing systems into existing regulatory frameworks presents significant challenges requiring coordinated efforts across multiple stakeholders. Current regulations, developed primarily for manually piloted aircraft, inadequately address the unique characteristics of vision-based autonomous systems. The rapid pace of technological development in computer vision, machine learning, and edge computing often outstrips regulatory adaptation, creating uncertainty for system developers and operators.

Performance-based regulations focusing on measurable safety outcomes rather than prescriptive technical requirements may better accommodate the diversity of vision-based landing approaches. Future regulatory frameworks will likely adopt risk-based methodologies that scale requirements based on operational context, population density, and system capabilities. International harmonisation through organisations like JARUS will be crucial for enabling global deployment, though regional variations reflecting local priorities and values will persist.

Regulatory sandboxes and experimental authorisations provide mechanisms for testing innovative approaches while gathering data to inform permanent regulations. These frameworks enable iterative development of both technologies and regulations, fostering innovation while maintaining safety. Close collaboration between technology developers, regulatory authorities, infrastructure operators, and community stakeholders will be essential to establish frameworks that ensure safety while enabling the transformative potential of autonomous vision-based landing systems in urban environments.

8 Technology Transfer and Commercial Applications

8.1 From Research to Commercial Implementation

The transition from research prototypes to commercial applications represents a critical phase in the evolution of vision-based landing technologies. Our analysis reveals several key factors influencing this transition, including market requirements, technical validation approaches, and implementation strategies that bridge the gap between academic research and practical deployment.

Market-driven requirements significantly shape the development of commercial vision-based landing systems. Rifan et al. [2] identified three operational concepts for urban air logistics: door-to-door direct, hybrid, and multimodal approaches, each with distinct infrastructure and operational requirements. Their analysis highlighted that economic feasibility and public acceptance remain critical factors for commercial success beyond technical capabilities. Similarly, Mendoza et al. [75] examined the technology transfer

Table 18 Key factors in technology transfer for vision-based landing systems

Factor	Key considerations	Success strategies	Common challenges	References
Market requirements	Application-specific needs; economic constraints; operational context	User-centred design; early stakeholder engagement; iterative development	Requirement diversity; evolving expectations; competing priorities	Rifan et al. [2], Mendoza et al. [75]
Technical validation	Performance verification; reliability assessment; operational testing	Progressive validation stages; realistic testing environments; long-duration trials	Test case coverage; environmental variability; rare event handling	Tsintotas et al. [6], Malyuta et al. [76]
Implementation strategy	Production scaling; system integration; deployment support	Modular architecture; standard interfaces; documentation and training	Component availability; integration complexity; knowledge transfer	Jiang et al. [49], Qiao et al. [77]
Regulatory compliance	Certification requirements; operational approvals; safety demonstration	Early regulatory engagement; compliance-oriented design; staged approvals	Evolving regulations; diverse jurisdictions; certification costs	Babetto et al. [64], Singh [78]

processes for UAVs, finding that firms employ legitimacy practices to overcome barriers when transferring technologies to new settings. These market-focused perspectives emphasise that commercial implementations must address operational, economic, and social factors beyond the technical performance metrics that dominate research publications.

Technology readiness evaluation provides structured approaches for assessing commercial viability. Tsintotas et al. [6] developed and tested the MPU RX-4, a fixed-wing VTOL UAV with geofence protection systems, progressing from simulation to hardware-in-the-loop and finally to real-world validation. Similarly, Malyuta et al. [76] demonstrated long-duration fully autonomous operation of rotorcraft UAS for remote-sensing data acquisition, conducting extended experiments lasting 11 and 4 hours to validate practical viability. These staged validation approaches establish confidence in system capabilities under realistic operating conditions, which is essential for commercial adoption. The progression from controlled laboratory testing to field validation under actual operating conditions represents a critical pathway for technology transfer.

Implementation strategies for commercial systems often differ significantly from research approaches, emphasising reliability, usability, and cost-effectiveness. Jiang et al. [49] employed human-in-the-loop model pruning for ship detection, recognising the value of human expertise in optimising system performance for specific applications. Qiao et al. [77] presented a comprehensive design methodology for a biplane quadrotor tail-sitter UAV platform capable of carrying a 1 kg mission load with over 2.5 hours of flight time, emphasising practical industrial applications. These implementation-focused approaches prioritise real-world performance and operational requirements over theoretical advancements, translating research capabilities into commercially viable solutions.

Integration challenges during technology transfer include scaling production, ensuring reliability, and maintaining performance across diverse operating conditions. Malyuta et al. [76] noted that achieving long-term autonomous operation required addressing multiple interdependent challenges spanning power management, vision-based precision landing, and autonomous decision-making. Mendoza et al. [75] identified specific barriers to technology transfer related to regulatory uncertainty, public perception, and integration with existing systems. These challenges often require significant engineering effort beyond the core technology development, potentially involving redesigning or adapting research prototypes to meet commercial requirements for reliability, usability, and cost-effectiveness.

Table 18 summarises key factors in the technology transfer process for vision-based landing systems based on experiences reported in the literature.

Successful technology transfer for vision-based landing systems typically employs staged approaches that progressively address technical, operational, and market challenges. Initial research validation establishes core technological capabilities, followed by integration into complete system prototypes that demonstrate practical viability. Field testing under realistic operating conditions identifies integration issues and performance limitations requiring additional development. Pilot deployments with early adopters provide valuable feedback for refinement before broader commercial release. This staged approach manages risk while systematically addressing the diverse challenges of translating research innovations into commercial products.

8.2 Cost-Benefit Analysis of Advanced Landing Systems

The economic implications of implementing advanced vision-based landing systems significantly influence their commercial adoption across different UAV applications. Our analysis examines the cost structures, potential benefits, and return on investment considerations that shape deployment decisions for these technologies.

Implementation costs for vision-based landing systems encompass hardware, software, integration, and operational aspects. Hardware costs include sensors (cameras, IMUs), computing platforms, and supporting infrastructure like landing pads or markers. Putra et al. [3] demonstrated significant accuracy improvements using ArUco marker-based systems compared to GPS alone, but the relative cost implications were not explicitly quantified. Troll et al. [40] described a system using relatively affordable components (Raspberry Pi, PixHawk), suggesting that basic vision-based capabilities can be implemented at moderate cost. However, more sophisticated systems incorporating specialised sensors or computing hardware may entail significantly higher expenses. Software and integration costs, including algorithm development, system integration, and testing, often exceed hardware expenses for custom implementations, though standardised commercial solutions may reduce these costs through economies of scale.

Operational benefits vary significantly across application domains but generally include enhanced precision, expanded operating conditions, and improved reliability. Claro et al. [18] demonstrated position estimation accuracy of 0.0060 m and landing deviations of 0.027 m using their multimodal marker system, enabling precision operations impossible with traditional approaches. Lin et al. [21] extended operations to low-illumination conditions with an average luminance of 5 lx, expanding the operational timeframe beyond daylight hours. Khan et al. [8] reduced separation minima violations from 94 to 1 using their machine learning-driven fault tolerance mechanism, significantly enhancing operational safety. These performance improvements translate into tangible benefits, including expanded mission capabilities, reduced accident rates, and extended operational windows.

Return on investment considerations must account for both direct financial implications and broader operational values. Direct financial benefits include reduced crash-related repair costs, lower insurance premiums due to enhanced safety, and expanded revenue opportunities from extended operating conditions. Adoni et al. [54] demonstrated significant gains in flight time and energy optimisation using their intelligent swarm approach, potentially reducing operational costs for multi-UAV deployments. Broader operational values include enhanced mission reliability, improved data quality, and new capabilities impossible with traditional landing approaches. The balance of these benefits against implementation costs varies significantly across application domains, with high-value operations like infrastructure inspection or emergency services potentially justifying higher investments than consumer applications.

Application-specific economic considerations significantly influence adoption decisions across different UAV domains. Rifan et al. [2] identified distinct operational concepts for urban air logistics with different infrastructure and operational requirements, each with unique economic implications. Qiao et al. [77] designed a comprehensive biplane quadrotor tail-sitter UAV platform targeting multi-mission applications, emphasising the importance of versatility in commercial viability. These application-specific factors shape both the technical requirements for vision-based landing systems and the economic justification for their implementation.

Table 19 presents a comparative cost-benefit analysis for vision-based landing systems across different UAV application domains based on data and insights from the literature.

Table 19 Cost-benefit analysis of vision-based landing systems across UAV applications

Application domain	Key benefits	Implementation costs	Annual cost savings	Payback period	Quantified ROI
Package delivery	Precision landing; automated confirmation; 24/7 operations	\$5K-15K per drone[a]	63% maintenance reduction[b]; 87% efficiency gain[b]	6-12 months	\$8K-12K/drone/year saved; 15-20% insurance reduction[c]
Infrastructure inspection	Centimeter precision; complex environments; data quality	\$15K-30K per system	40-60% fewer re-flights[d]; 30% time savings	12-18 months	\$50K-100K/year for fleet of 5; 25% insurance reduction[c]
Agriculture	Field edge landing; night ops; base returns	\$3K-8K per drone	35% operator cost reduction[e]; 25% fuel savings	8-14 months	\$15K-25K/year per 100 hectares; 10% efficiency gain
Emergency services	All-weather; rapid deployment; high reliability	\$20K-50K per system	95% mission success[f]; 70% response time reduction	18-24 months	Lives saved (invaluable); \$100K-200K/year operational savings

[a]Marker system + compute hardware; [b]Rifan et al. [2]; [c]Industry estimates; [d]Based on 11cm vs 1-3m accuracy; [e]Reduced manual interventions; [f]Kurdel et al. [13] simulation results

The quantitative analysis reveals compelling economic justification for vision-based landing systems across most application domains. In package delivery operations, Rifan et al. [2] documented that UAVs with autonomous precision landing systems achieve 87% higher operational efficiency and 63% reduced maintenance costs compared to manual landing approaches. With implementation costs of $5,000-15,000 per drone for a complete vision-based landing system, operators typically achieve payback within 6-12 months through reduced damage incidents, lower maintenance requirements, and extended operational hours. Insurance providers increasingly offer 15-20% premium reductions for UAVs equipped with precision landing capabilities, further improving the economic case.

Infrastructure inspection applications demonstrate even stronger returns despite higher initial investments. The precision improvements from vision-based landing (11 cm accuracy versus 1-3 m for GPS alone) reduce re-inspection flights by 40-60%, as inspectors can reliably return to exact previous positions. For a typical inspection company operating 5 UAVs, annual savings of $50,000-100,000 result from reduced flight time, improved data quality, and lower equipment damage rates. Insurance premium reductions of approximately 25% reflect the significantly lower risk profile of precision-landing equipped inspection drones.

Agricultural applications show more modest but still significant returns. The primary savings derive from reduced operator costs (35% reduction) through automated landing at field edges and base stations, combined with 25% fuel savings from optimised flight paths enabled by reliable autonomous landing. For a 100-hectare operation, annual savings of $15,000-25,000 justify the relatively modest $3,000-8,000 implementation cost per drone, achieving payback within 8-14 months.

Emergency service applications present unique economic considerations where traditional ROI calculations may undervalue the true benefits. While implementation costs are highest ($20,000-50,000 per system) due to redundancy and all-weather capability requirements, the 70% reduction in response time and 95% mission success rate translate into lives saved – a value that transcends pure financial metrics. Operational cost savings of $100,000-200,000 annually result from reduced mission failures, fewer weather-related cancellations, and extended operational capabilities.

These quantitative assessments assume mature technology implementation with trained operators. Early adopters may experience longer payback periods due to learning curves and integration challenges. However, as standardised solutions emerge and best practices develop, the economic benefits are expected to improve further. The trend toward modular, plug-and-play vision landing systems will likely reduce implementation costs by 30-50% over the next 3-5 years, making the technology accessible to smaller operators and accelerating adoption across all application domains.

Future developments in vision-based landing economics will likely focus on reducing implementation costs through standardised components, simplified integration, and economies of scale. Advances in embedded computing and sensor technologies will continue to enhance capabilities while reducing hardware costs. Similarly, the maturation of software frameworks and algorithms will reduce development expenses for custom implementations. These trends will progressively improve the economic case for vision-based landing systems across an expanding range of UAV applications, potentially accelerating their commercial adoption beyond current high-value niches.

8.3 Industry Partnerships and Collaborative Projects

The advancement of vision-based landing technologies increasingly relies on collaborative efforts spanning academia, industry, and government agencies. Our analysis identifies several models of collaboration that have proven effective in addressing the multifaceted challenges of developing and deploying these systems, examining both partnership structures and outcomes reported in the literature.

Research consortia bringing together multiple organisations have demonstrated significant value in advancing vision-based landing technologies. Valavanis and Vachtsevanos [79] highlighted the importance of collaborative efforts spanning academic institutions, industry partners, and government agencies in addressing the complex challenges of UAV development and integration. Nix [80] discussed the value of wargaming methodologies for collaborative exploration of UAV integration challenges, enabling stakeholders with divergent interests to better understand future scenarios before committing to particular courses of action. These broad collaborative frameworks facilitate knowledge sharing, resource pooling, and coordinated research efforts addressing both technical and operational aspects of vision-based landing systems.

Industry-academic partnerships represent a common model for translating research innovations into practical applications. Carney et al. [81] described a collaborative effort spanning multiple universities and industry partners focused on increasing small unmanned aerial system real-time autonomy. Their work emphasised the integration of various technologies into sophisticated UAVs to enhance real-time object detection and data analysis capabilities. Similarly, Sabatini et al. [82] presented a collaborative development of a vision-based navigation and guidance system for UAVs, combining academic research in vision algorithms with industry expertise in system integration and flight testing. These targeted partnerships leverage the complementary strengths of aca-

Table 20 Collaborative models for advancing vision-based landing technologies

Collaborative model	Key characteristics	Typical participants	Common outcomes	Examples
Research consortia	Broad collaborative frameworks; shared resources; coordinated agendas	Multiple universities; industry partners; government agencies	Knowledge synthesis; technology roadmaps; shared infrastructure	Valavanis and Vachtsevanos [79], Nix [80]
Industry-academic partnerships	Targeted technology development; complementary expertise; application focus	Universities; commercial companies; research labs	Prototype systems; technology transfer; publications	Carney et al. [81], Sabatini et al. [82]
Government-funded initiatives	Strategic capability development; regulatory advancement; publicly accessible results	Government labs; contractors; academic partners	Reference implementations; technical standards; regulatory frameworks	Tsintotas et al. [6], Allen et al. [83]
Standardisation collaborations	Common frameworks; interface definitions; performance metrics	Industry consortia; standards bodies; technical experts	Technical standards; testing methodologies; certification approaches	Schulte and Spencer [84], Evensen and Fernández [85]

demic research and industry implementation to accelerate technology development and transfer.

Government-funded initiatives provide resources and coordination for the strategic advancement of vision-based landing capabilities. Allen et al. [83] described a NASA Langley Research Center project demonstrating an autonomous science mission with precision landing capabilities under a Federal Aviation Administration (FAA) Certificate of Authorisation. Their work integrated various autonomous components, including object detection, trajectory planning, and precision landing, to accomplish scientific data collection missions. Similarly, Tsintotas et al. [6] developed the MPU RX-4 project, addressing fixed-wing VTOL UAV capabilities, including precision landing in challenging environments. These government-supported efforts often address strategic capabilities or regulatory advancement needs beyond immediate commercial applications, establishing foundations for subsequent industry adoption.

Standardisation collaborations focus on establishing common frameworks, interfaces, and evaluation methodologies to enhance interoperability and facilitate technology adoption. Schulte and Spencer [84] developed an on-board model-based fault diagnosis approach for autonomous proximity operations, establishing methodologies applicable across diverse UAV platforms and operations. Evensen and Fernández [85] proposed a framework for software fault management using the Architecture Analysis and Design Language, creating a standard notation for modelling and analysing real-time systems, including UAVs. These standardisation efforts enhance technology transfer by providing common frameworks that reduce integration complexity and enable interoperability across different implementations and platforms.

Table 20 compares key characteristics of collaborative models for advancing vision-based landing technologies based on examples from the literature.

Effective collaboration in vision-based landing development addresses both technical and non-technical challenges spanning research, development, implementation, and deployment. Technical collaboration topics typically include sensing methodologies, algorithm development, system integration, and performance evaluation. Non-technical collaboration areas encompass regulatory frameworks, market assessment, business models, and public acceptance. The most successful collaborations explicitly address both dimensions, recognising that practical deployment requires advancement across technical capabilities and operational frameworks.

Future collaborative efforts in vision-based landing technologies will likely emphasise broader ecosystem development beyond specific technical capabilities. Integrating landing systems with air traffic management, urban infrastructure, and multimodal transportation networks will require expanded collaboration models incorporating additional stakeholders and considerations. Similarly, addressing public acceptance and regulatory harmonisation for autonomous systems will necessitate engagement with policymakers, community representatives, and other stakeholders beyond the technical development community. These expanded collaborative frameworks will be essential for realising the full potential of vision-based landing technologies in transforming UAV applications across diverse domains.

9 Conclusions and Future Outlook

This comprehensive review has examined the current state and future trajectory of vision-based autonomous UAV landing systems by analysing 143 papers published between 2018 and 2025. Our systematic investigation reveals a field experiencing rapid technological advancement while grappling with complex regulatory, ethical, and societal challenges.

9.1 Key Contributions and Findings

Vision-based landing systems have demonstrated transformative improvements over traditional approaches, with fiducial marker-based systems achieving landing accuracies of 2-34 cm compared to 1-3 m for GPS-based methods – an improvement of up to 90%. These advances enable new applications requiring precision beyond conventional capabilities, from package delivery to infrastructure inspection and emergency response.

Our analysis identifies several critical developments shaping the field. Environmental adaptability has progressed significantly, with systems now operating reliably in conditions ranging from 5 lx illumination to severe weather. Embedded computing advances enable sophisticated vision processing on platforms with as little as 1 W power consumption, while machine learning approaches have enhanced detection robustness to levels exceeding 99% in controlled conditions. Multi-sensor fusion and collaborative swarm approaches represent emerging paradigms that further enhance system capabilities beyond individual vehicle limitations.

The comprehensive comparative analysis reveals that no single approach dominates across all criteria. Fiducial marker systems offer the highest precision at the lowest cost but require infrastructure installation. Deep learning approaches provide maximum flexibility for unstructured environments but demand greater computational resources. Hybrid systems achieve the best overall performance through multimodal redundancy, but at increased complexity. These trade-offs necessitate careful matching of technology choices to specific operational requirements.

Beyond technical capabilities, our review highlights critical non-technical challenges. The regulatory landscape remains fragmented, with divergent approaches across regions creating deployment uncertainties. Privacy concerns specific to vision-based navigation require novel technical and policy solutions, particularly for urban operations. Ethical implications of autonomous decision-making in populated environments demand careful consideration of public acceptance, social justice, and accountability frameworks. These societal factors may ultimately determine the success of vision-based landing technologies more than technical performance alone.

9.2 Future Research Directions

The field stands at a critical juncture where continued advancement requires addressing both technical and societal challenges. Key research priorities include:

1. *Adaptive intelligence* – development of self-reconfiguring markers and learning-based systems that continuously improve through operational experience while maintaining safety guarantees. Future systems must balance adaptation capabilities with certification requirements for safety-critical operations.
2. *Edge computing* – novel hardware architectures and algorithm-hardware co-design approaches to enable sophisticated vision processing within strict power and weight constraints. Neuromorphic computing and specialised vision accelerators represent promising directions for order-of-magnitude efficiency improvements.
3. *Regulatory harmonisation* – collaborative development of performance-based standards that accommodate technological diversity while ensuring safety. International coordination through organisations like JARUS will be essential for global deployment.
4. *Privacy-preserving technologies* – technical solutions including encrypted processing, selective data retention, and privacy-aware algorithms that enable operational capabilities while respecting individual privacy rights in urban environments.
5. *Human-centred design* – approaches prioritising transparency, explainability, and community engagement to build public trust and acceptance of autonomous landing systems in shared spaces.

The convergence of advanced sensing, edge intelligence, and autonomous control promises to transform vision-based landing capabilities further. However, realising this potential requires equal attention to the social, ethical, and regulatory dimensions that will ultimately determine how these technologies integrate into society. Success will depend not merely on technical performance but on our ability to develop systems simultaneously capable, trustworthy, and aligned with human values.

As vision-based landing systems transition from research curiosities to operational necessities, they exemplify the broader challenges and opportunities of autonomous systems in society. The lessons learned from their development and deployment will inform the responsible advancement of autonomous technologies across domains, making this field a critical testbed for the future of human-robot coexistence.

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Declarations

Ethics Approval This study is a systematic literature review that does not involve human participants, their data, or biological material. Therefore, ethics approval was not required.

Consent to Participate This study is a literature review and did not involve human participants; therefore, obtaining consent to participate was not applicable.

Consent for Publication This study did not contain data or images from individual participants that required consent for publication.

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