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Drone-Sharing Models for Inclusive Precision Agriculture

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Abstract

Unmanned aerial vehicles have expanded the technical possibilities of precision agriculture by enabling high-resolution crop monitoring, stress detection, field mapping, spraying, and other spatially targeted operations. Their benefits, however, can remain concentrated among larger or better-capitalized farms when access depends on individual ownership of aircraft, sensors, software, trained operators, and data-processing infrastructure. This study develops a simulation-based framework for evaluating drone-sharing models as mechanisms for more inclusive precision agriculture. Five access arrangements are compared: individual ownership, peer-to-peer rental, cooperative sharing, custom hiring centers, and drone-as-a-service provision. An Inclusive Drone Access Index is constructed using affordability, operational timeliness, technical-service capacity, farmer inclusion, and data-governance quality. The simulated index increases from 50.4 under individual ownership to 58.1 for peer rental, 75.8 for cooperative sharing, 82.9 for custom hiring centers, and 88.3 for drone-as-a-service.

The analysis indicates that sharing can reduce the fixed-cost barrier to precision agriculture, but affordability alone does not guarantee inclusion. Seasonal service congestion, operator shortages, inaccessible digital interfaces, weak agronomic interpretation, uncertain data rights, and exclusion of remote or very small farms can reproduce inequality even under nominally shared systems. Cooperative and custom-hiring arrangements offer stronger potential when booking rules, pricing, service territories, operator training, and data responsibilities are transparent. Drone-as-a-service performs most strongly in the simulation because specialized equipment, operators, maintenance, analytics, and farmer-facing interpretation can be combined within one service relationship. The study concludes that drone sharing should be designed as an inclusive agricultural service system rather than simply as equipment rental. Effective models require farmer-oriented scheduling, transparent pricing, locally available operators, interoperable data, accountable data governance, and deliberate safeguards for small and resource-constrained producers.

Keywords: agricultural drones, precision agriculture, drone sharing, smallholder farming, custom hiring, digital agriculture, technology inclusion, drone-as-a-service

1. Introduction

Precision agriculture seeks to improve farm decisions by recognizing spatial and temporal variability within agricultural production systems. Remote sensing, positioning systems, variable-rate application, digital mapping, sensors, and data analytics can enable farmers to direct interventions toward the locations and times at which they are most useful. Unmanned aerial vehicles, commonly referred to as drones, have become particularly relevant because they can generate field-scale imagery at high spatial and temporal resolution without requiring permanent sensing infrastructure. Reviews by Maes and Steppe and by Mukherjee and colleagues document applications ranging from crop-vigor assessment and drought detection to weed identification, nutrient-status assessment, phenotyping, and other field-monitoring tasks.

The technical capability of a drone system does not, however, determine whether farmers can use it productively. Access may require the aircraft itself, appropriate sensors, replacement batteries, maintenance, trained pilots, regulatory compliance, image-processing software, cloud or local computing capacity, and agronomic expertise capable of converting imagery into management recommendations. Finger and colleagues observe more broadly that precision-farming adoption has historically been concentrated among larger farms even though its production and environmental benefits may also be relevant to small-scale agriculture. The UNDP guidance on precision agriculture for smallholder farmers similarly identifies business models, digital skills, technical infrastructure, and operational feasibility as central considerations rather than treating hardware affordability as the only adoption issue.

Individual ownership can intensify these barriers where agricultural holdings are small or drone demand is highly seasonal. A farmer may need aerial assessment only at selected crop stages, after extreme weather, or during a narrow spraying period, leaving expensive equipment underused for much of the year. Economic studies of agricultural automation reinforce the general principle that advanced equipment adoption is closely related to utilization rates and the capacity to justify fixed investment. Lowenberg-DeBoer and colleagues emphasize that technical feasibility is insufficient when equipment does not generate an economically credible production system. Shared access can alter this equation by spreading capital, maintenance, expertise, and software costs across a larger service base.

Agricultural machinery sharing already provides an institutional precedent. Custom hiring centers have been used to make equipment available to farmers who cannot economically justify direct purchase. CGIAR documentation of custom hiring centers describes rental-based access to machinery as a mechanism for improving technology availability among small and marginal farmers, while government-supported machinery-sharing systems have similarly attempted to connect farmers with equipment available for hire. Drone technologies create an opportunity to extend this principle from conventional mechanization to data-intensive precision services, but they also introduce additional requirements related to aviation regulation, remote sensing, digital interpretation, and agricultural data governance.

The present study examines whether alternative drone-sharing arrangements can create more inclusive pathways into precision agriculture. It does not present observations from an implemented drone-sharing program, farmer survey, or commercial service database. Instead, five access models are compared through a transparent simulation framework. The analysis considers affordability together with timeliness, technical capacity, inclusion, and data governance because a low-cost service that arrives after the agronomic decision window, provides uninterpretable imagery, or requires farmers to surrender poorly defined data rights cannot be considered genuinely inclusive. The central proposition is that drone democratization depends less on the number of drones distributed across rural areas than on the quality of the service institutions through which farmers can convert aerial technology into timely and trustworthy agronomic decisions.

2. Objectives of the Study

2.1 Assessing the Inclusiveness of Alternative Drone-Access Models

The first objective is to compare the inclusiveness of individual ownership, peer rental, cooperative sharing, custom hiring centers, and drone-as-a-service arrangements. The analysis evaluates whether each model can lower barriers that arise from capital requirements, maintenance, operator certification, software, and specialized sensing equipment.

Inclusiveness is defined more broadly than the availability of a drone within a geographic area. A model is considered more inclusive when farmers with smaller holdings, limited capital, lower digital literacy, or irregular service demand can obtain technically competent services without bearing disproportionate costs or administrative burdens.

2.2 Examining Service Reliability and Shared Technical Capacity

The second objective is to assess whether sharing arrangements can preserve the timeliness required for precision agriculture. Agricultural drone demand is often synchronized with crop growth stages, pest outbreaks, weather events, and short spraying windows. A shared aircraft that is inexpensive but unavailable during the critical decision period may generate little practical value.

The study consequently evaluates operator availability, maintenance capacity, scheduling, analytics, and service reliability. The model distinguishes equipment sharing from capability sharing because precision agriculture requires more than access to an aircraft. Farmers must also receive usable information or correctly executed field operations.

2.3 Developing an Inclusive Governance Framework for Shared Drone Services

The third objective is to identify governance conditions under which drone sharing can remain accessible, trustworthy, and agriculturally useful. These conditions include transparent pricing, nondiscriminatory booking procedures, understandable data agreements, geographical coverage, quality assurance, operator accountability, and mechanisms for farmer feedback.

Particular attention is given to agricultural data because aerial imagery may reveal crop condition, field boundaries, production patterns, and management characteristics. Research on smart farming demonstrates that uncertainty concerning data ownership, access, reuse, privacy, and benefit sharing can weaken farmer trust in digital technologies.

3. Review of Literature

3.1 Drone Capability and the Precision-Agriculture Value Proposition

Agricultural UAV research has developed from relatively simple aerial imaging toward multispectral, thermal, hyperspectral, and automated field applications. Mogili and Deepak describe crop monitoring and spraying among prominent agricultural uses, while Mukherjee and colleagues review UAV sensing architectures for precision agriculture and highlight their maneuverability and ability to collect high-resolution local information.

Maes and Steppe show that UAV remote sensing can support drought-stress assessment, weed detection, nutrient evaluation, yield-related analysis, and other crop-management functions. The value of UAVs arises partly from their combination of fine spatial resolution and flexible acquisition timing, allowing information to be collected when satellite availability or spatial resolution is unsuitable for a particular farm decision. Radoglou-Grammatikis and colleagues similarly identify a broad portfolio of monitoring and spraying applications within precision agriculture.

Yet high-resolution data are valuable only when they influence management. Agricultural imagery may require georeferencing, radiometric correction, vegetation-index calculation, classification, interpretation, or integration with field observations before a farmer can decide whether a crop area requires irrigation, nutrient intervention, pest control, or further inspection. A shared-drone model that supplies images without actionable interpretation may therefore transfer technical complexity from equipment ownership to information use rather than resolving the underlying access problem.

3.2 Cost, Scale, and the Logic of Shared Access

Precision-farming economics is strongly influenced by farm scale, frequency of use, equipment utilization, learning costs, and the value created by improved management. Finger and colleagues note that precision agriculture can reduce inefficient input use and associated environmental costs, yet adoption incentives vary across farming systems. Weersink and colleagues similarly identify data interpretation and farmer capability as barriers to realizing the economic promise of increasingly inexpensive agricultural data collection.

These conditions create a strong theoretical rationale for shared access. Where a farmer needs a specialized technology only a few times per season, purchasing the entire technological stack may produce a poor utilization rate. Sharing allows the fixed cost of equipment and expertise to be distributed across multiple farms. The same logic underpins traditional machinery rental and custom-hiring systems.

CGIAR's experience with custom hiring centers demonstrates how rental institutions can provide access to costly agricultural equipment that small farmers may not be able to purchase individually. The broader model is directly relevant to drones, although UAV services require a stronger knowledge component than many mechanical implements. The shared asset may consist not only of the drone but also of a certified operator, sensor package, image-processing system, agronomic interpretation, insurance, maintenance, and regulatory administration.

Several organizational alternatives are consequently possible. Peer-to-peer rental minimizes institutional overhead but can provide inconsistent maintenance and operator quality. Cooperatives distribute ownership among members and can build collective capability but require effective governance. Custom hiring centers can professionalize scheduling and equipment management. Drone-as-a-service goes further by selling the completed agricultural service rather than access to the aircraft itself.

3.3 Digital Inclusion, Regulation, and Agricultural Data Trust

Technological inclusion is not synonymous with lower equipment prices. Farmers may encounter barriers involving literacy, electricity, internet access, smartphone ownership, language, technical support, service-provider distance, or confidence in unfamiliar technologies. UNDP's smallholder precision-agriculture guidance explicitly treats appropriate business models, infrastructure, and digital skills as critical components of technology deployment.

Drone operation also takes place within aviation and privacy regimes. Ayamga, Tekinerdogan, and Kassahun show that regulation can significantly influence agricultural UAV deployment and that complex licensing systems can create barriers to effective use. Their analysis also highlights privacy and data-protection considerations surrounding drone operations. Shared-service models may partially reduce this burden by concentrating regulatory responsibility among trained providers rather than requiring every farmer to become an aircraft operator.

Data governance creates a parallel institutional challenge. Wiseman and colleagues found that unclear arrangements surrounding ownership, access, privacy, liability, and data sharing contribute to farmer reluctance toward smart-farming technologies. Jakku and colleagues likewise identify transparency, trust, and benefit distribution as central to farmer perceptions of agricultural data systems. These concerns are particularly relevant to drone sharing because one service provider may collect high-resolution information across many farms.

An inclusive drone-sharing institution should therefore clarify who may access raw imagery, processed maps, field boundaries, agronomic recommendations, and aggregated datasets. Farmers should understand whether data are retained after a mission, whether third parties can use them, and whether consent can be withdrawn. These governance questions are not secondary legal details; they influence willingness to participate and the distribution of value generated from digital agriculture.

4. Research Methodology

4.1 Simulation Design and Comparative Access Models

The study uses a simulation-based multicriteria design. No real farmers, drone companies, cooperatives, custom-hiring centers, or flight missions constitute the study sample. Numerical scores are hypothetical values developed to demonstrate a structured method for comparing access models.

Five arrangements are evaluated. Individual ownership represents a farmer purchasing and managing the drone system directly. Peer-to-peer rental represents informal or semi-formal access to a drone owned by another farmer or local operator. Cooperative sharing distributes ownership and governance among a farmer group. Custom hiring center access places drones within an organized equipment-rental institution. Drone-as-a-service provides the completed sensing, mapping, spraying, or analytical service through a specialized provider.

These models are not assumed to be mutually exclusive in actual agricultural systems. A cooperative may purchase services from a specialized provider, while a custom hiring center may contract private operators. The classification is used to distinguish the principal locus of ownership, operational responsibility, and service delivery.

4.2 Construction of the Inclusive Drone Access Index

An Inclusive Drone Access Index (IDAI) was developed to compare the five models. The index recognizes that affordability is important but insufficient. Operational delays, poor technical support, exclusion of remote farms, or weak data governance can reduce practical access even when prices are low.

Table 1: Inclusive Drone Access Index criteria and weights

Criterion	Interpretation	Weight
Affordability	Capacity to minimize farmer-level capital, maintenance, software, and training burdens	0.25
Operational timeliness	Probability that services can be delivered within relevant crop and weather decision windows	0.20
Technical-service capacity	Availability of competent operators, maintenance, sensors, processing, and agronomic interpretation	0.20
Farmer inclusion	Accessibility for small farms, remote users, lower-digital-literacy farmers, and infrequent users	0.20
Data-governance quality	Transparency concerning data access, storage, reuse, consent, confidentiality, and accountability	0.15

The index is calculated as:

$$IDAI = 0.25A + 0.20T + 0.20C + 0.20I + 0.15G$$

where A represents affordability, T operational timeliness, C technical capacity, I farmer inclusion, and G data governance.

Affordability receives the highest individual weight because ownership cost is one of the most direct barriers separating small producers from advanced agricultural equipment. The remaining weights are intentionally substantial because a cheap but unreliable or inaccessible service does not constitute effective inclusion.

4.3 Scoring Procedure and Research Integrity

Each model was assigned standardized scores between zero and one hundred according to its conceptual characteristics. Individual ownership receives a relatively high timeliness score because the farmer controls deployment once equipment and skills are available, but affordability and inclusion remain low. Shared models receive progressively higher affordability scores because fixed costs are distributed across users.

Drone-as-a-service receives the highest technical-service score because the model assumes professionalized provision combining operation, maintenance, sensing, processing, and farmer-oriented output. Custom hiring centers receive a slightly lower score because equipment-rental organizations can vary in their analytical capacity. Cooperative sharing performs strongly where members build collective expertise but remains dependent on governance and service coordination.

These scores do not represent measured adoption rates, profitability, yield effects, or actual service prices. An empirical version of the framework would require cost records, farm-level service histories, booking delays, mission completion rates, user demographics, operator qualifications, data-policy audits, and farmer satisfaction measures.

5. Analysis

5.1 Comparative Performance of Drone-Sharing Arrangements

The simulation produces a substantial difference between individually owned technology and organized shared-service models. Individual ownership achieves an IDAI of 50.4. Its principal advantage is operational autonomy: a capable farmer can deploy the drone according to field conditions rather than waiting for a provider. Its disadvantage is the concentration of cost, maintenance, regulatory responsibility, and technical-learning requirements within a single farm.

Peer-to-peer rental increases the simulated index to 58.1. It lowers direct investment but does not automatically provide professional maintenance or analytical capability. Informal arrangements may work effectively in areas with strong farmer networks, but reliability can vary when equipment is simultaneously required across neighboring farms.

Table 2: Simulated inclusive-access performance of alternative drone models

Access model	Affordability	Timeliness	Technical capacity	Farmer inclusion	Data governance	IDAI
Individual ownership	30	82	52	34	62	50.4
Peer-to-peer rental	58	64	54	55	60	58.1
Cooperative sharing	78	72	75	76	78	75.8
Custom hiring center	86	82	84	84	76	82.9
Drone-as-a-service	90	88	92	89	80	88.3

Note: All values are hypothetical simulation scores developed for methodological illustration and are not empirical measurements.

Cooperative sharing produces a markedly stronger score of 75.8. Collective ownership reduces the capital burden while allowing farmers to participate in governance and retain a closer connection to the asset. However, the cooperative must resolve scheduling, investment, maintenance, operator compensation, and membership responsibilities.

Custom hiring centers reach 82.9, reflecting their potential to institutionalize equipment access. Existing agricultural experience demonstrates that rental centers can lower mechanization barriers for small and marginal farmers. A drone-enabled center could extend this model by maintaining several sensor or aircraft configurations and assigning trained operators according to demand.

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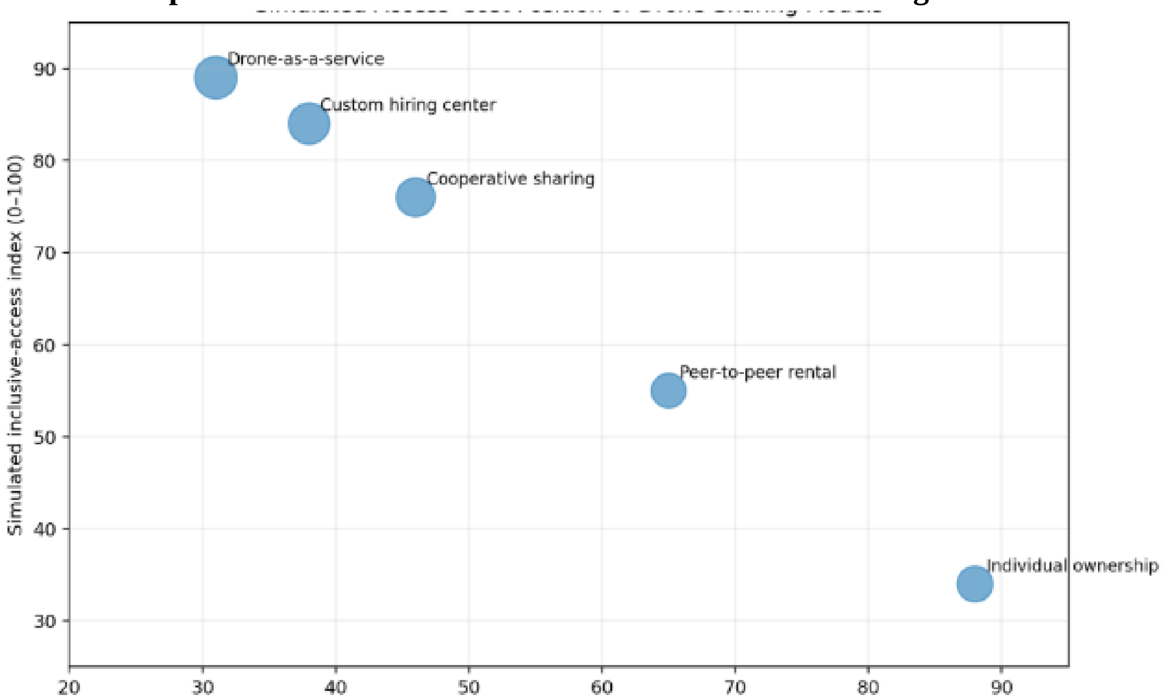
Drone-as-a-service obtains the highest simulated IDAI at 88.3. The model shifts the farmer's purchase decision from acquiring a complex technology to obtaining an agricultural outcome. Instead of buying a multispectral drone and learning processing software, a farmer might purchase a crop-stress survey covering a specified area and receive an interpreted management map.

5.2 Cost Burden and Inclusive Access

The simulated graph examines the relationship between farmer-level cost burden and inclusive access. Individual ownership occupies the least favorable position, combining a cost-burden index of 88 with an inclusive-access index of 34. Peer rental reduces the burden but provides only moderate inclusion. Cooperative, custom-hiring, and service-based arrangements move toward lower individual cost and higher access.

Graph 1: Simulated Access–Cost Position of Drone-Sharing Models



Source: Author's simulation developed for methodological illustration. Bubble size represents simulated service reliability.

The pattern illustrates why the economics of advanced agricultural equipment should be evaluated through utilization rather than purchase price alone. Equipment that remains idle for much of the year imposes a high fixed cost per useful mission. Shared services can increase utilization across farms, potentially allowing better sensors, maintenance, and professional operators to be supported from a common revenue base.

The relationship is nevertheless not automatically linear. A highly centralized service may reduce equipment cost while increasing travel time or limiting service during peak demand. The optimal sharing scale therefore depends on crop calendars, farm density, road access, mission duration, weather, regulatory conditions, and the number of aircraft and operators available.

5.3 Inclusion Beyond Equipment Availability

The analysis indicates that shared equipment should be distinguished from shared precision-agriculture capability. A farmer can technically obtain a drone flight yet remain excluded from the value of precision agriculture when the resulting maps are too complex to interpret. Weersink and colleagues identify interpretation and decision support as important challenges within data-intensive agriculture.

An inclusive service should therefore translate aerial data into agronomic information appropriate to the user's decision. Depending on the application, this might mean identifying field zones requiring ground inspection, preparing a prescription layer, estimating crop variability, documenting storm damage, or performing an accurately scheduled spraying operation. Farmers should not be required to become remote-sensing specialists merely to participate in precision agriculture.

Geographical inclusion must also be considered. Service providers may preferentially target large farms clustered near roads because transaction costs are lower. Small, dispersed, or remote farmers can consequently remain underserved even though a shared system exists. Inclusion metrics should therefore evaluate who actually receives service, not merely whether a drone provider is operating in the district.

6. Discussion

6.1 From Drone Ownership to Precision-Agriculture Services

The principal implication of the study is that individual ownership should not be treated as the default measure of drone adoption. A farmer can benefit from UAV-based precision agriculture without owning an aircraft, just as farmers can benefit from laboratories, harvesting equipment, veterinary expertise, or financial services without owning the underlying infrastructure.

This distinction is particularly important for small farms. The UNDP smallholder precision-agriculture framework recognizes the importance of suitable business models alongside the technical feasibility of digital tools. Custom-hiring experience similarly demonstrates that rental institutions can expand access to otherwise expensive agricultural technologies.

Drone-as-a-service extends the sharing logic by bundling complementary capabilities. Flight planning, aircraft compliance, sensor calibration, battery management, image processing, analytics, and agronomic communication can be provided by specialists. This specialization can improve reliability while allowing farmers to concentrate on production decisions.

However, service provision can also create dependency. If only one provider operates in a region, farmers may face high prices, delays, proprietary data formats, or difficulty moving historical data to another service. Competition, interoperability, transparent contracts, and farmer access to their own outputs therefore remain important.

6.2 Scheduling, Scale, and the Risk of Shared-Service Congestion

Agricultural sharing has a temporal problem that differs from many consumer-sharing systems. Neighboring farmers often need the same technology at approximately the same time. Pest outbreaks, flowering stages, rainfall events, fertilizer windows, and crop stress can synchronize demand across an entire farming area.

A poorly designed sharing system may therefore fail precisely when its value is greatest. Cooperative and custom-hiring institutions need priority rules, advance reservation mechanisms, emergency allocation procedures, realistic service-area boundaries, and sufficient equipment redundancy. Service quality should be monitored through actual waiting time rather than equipment numbers alone.

Crop sensitivity can be incorporated into scheduling. A mission supporting time-critical disease detection may reasonably receive different priority from routine documentation. Similarly, spraying services affected by wind conditions require greater operational flexibility than mapping tasks that can tolerate a longer scheduling window.

Providers can also manage congestion by developing local operator networks rather than concentrating expertise at a distant regional center. Standardized training, maintenance protocols, and quality assurance can allow multiple operators to provide consistent services while maintaining sufficient local capacity during peak periods.

6.3 Farmer Agency, Data Rights, and Inclusive Digital Governance

Drone sharing changes who controls agricultural data. Under individual ownership, the farmer may retain direct custody of imagery, although cloud software can still create third-party data relationships. Under a service model, an external provider typically collects and processes the information. This arrangement can be efficient, but it also creates questions concerning access and reuse.

Wiseman and colleagues demonstrate that farmer trust can be weakened by unclear data relationships, including uncertainty over ownership, portability, privacy, and third-party access. Jakku and colleagues further emphasize transparency and benefit sharing in smart-farming systems. A drone-sharing agreement should consequently explain data practices in language that farmers can understand.

At minimum, farmers should know what information is collected, how long it is retained, whether it can be used to train analytical models, whether it is combined with data from other farms, who can purchase or access aggregated information, and what happens when the farmer changes service provider. Data portability is particularly important because historical imagery can acquire greater value when compared across seasons.

Inclusive governance also requires farmers to retain meaningful decision authority. A technologically sophisticated provider should not convert precision agriculture into a system in which recommendations are delivered as opaque instructions. Farmers possess contextual information regarding field history, varietal performance, irrigation, labor, pest pressure, and economic constraints that may not be visible in aerial imagery. The strongest model therefore combines analytical expertise with farmer interpretation rather than replacing farmer judgment.

7. Conclusion

Drone-sharing models provide a credible pathway for extending precision-agriculture capability beyond farms able to purchase and independently operate complete UAV systems. The technology has well-documented potential for high-resolution crop sensing, field monitoring, and targeted agricultural operations, but capital cost, expertise, analytics, regulation, and data management can restrict effective adoption. Evaluating inclusion solely through the declining price of drone hardware therefore understates the institutional challenge.

The simulation demonstrates progressively stronger inclusive-access performance as the model shifts from individual ownership toward organized collective and service-based provision. Individual ownership achieves an illustrative IDAI of 50.4, compared with 75.8 for cooperative sharing, 82.9 for custom hiring, and 88.3 for drone-as-a-service. These values are not empirical estimates, but they demonstrate how sharing can distribute both financial and knowledge-intensive components of precision agriculture.

The strongest models do more than rent aircraft. They provide reliable operators, maintenance, appropriate sensors, regulatory compliance, actionable analysis, transparent pricing, farmer-oriented scheduling, and responsible data governance. Their success should be evaluated by whether small and resource-constrained farmers receive useful services at appropriate times, not by the number of drones purchased or flights completed. Particular attention is required to avoid service concentration among large farms and accessible locations.

Future empirical research should compare actual cooperative, custom-hiring, private-service, and individual-ownership models using cost per hectare, mission waiting time, equipment utilization, operator productivity, service failure, farmer retention, smallholder participation, data portability, agronomic decision quality, input savings, and profitability. Longitudinal evaluation across several crop seasons would reveal whether sharing institutions remain reliable when demand expands beyond pilot scale. Such research could move agricultural drone policy away from technology distribution and toward a more durable objective: ensuring that precision-agriculture intelligence becomes accessible as a trustworthy rural service rather than a technological privilege attached to farm size or purchasing power.

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