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5G-Enabled Drone System: Quantitative Feasibility and Investment Strategy

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ABSTRACT

This study provides an evidence-based decision framework and a quantitative feasibility assessment of a 5G-based drone system in precision agriculture. Uplink transmission times under 4G and several 5G scenarios were simulated using a data-driven model based on actual drone image transmissions (0.574 GB per mission). The simulation showed a more than 90% increase in performance using 5G, which successfully addresses the 4G transmission constraint by reducing the average transmission delay ($\tau1$) from 1,205 seconds (20.1 minutes) under 4G to between 61 and 96 seconds (1-1.6 minutes) under 5G. However, a rural edge coverage stress test (100 simulations) showed a high standard deviation in $\tau1$ (approximately 43 seconds), which resulted in a long tail in the latency distribution, quantifying the unreliability of the network as a primary business risk. A technical artefact, the MNDVI Heatmap algorithm, validated the system's ability to extract valuable information from low-cost RGB sensors. To address the high capital costs, a conditional adoption approach using a Hybrid Network Architecture (5G as a service for bandwidth, a mesh network for C2 reliability) and a Drone as a Service (DaaS) business model is proposed.

Keywords: Drone, Agriculture, 5G.

Categories: H.3.1, H.3.2, H.3.3, H.3.7, H.5.1

1 Introduction

Precision agriculture has been increasingly using high-resolution and real-time monitoring for increased productivity and resource utilization efficiency. Unmanned aerial vehicles (UAVs) have emerged as a major enabler for precision agriculture due to their flexibility in collecting high-resolution field data on a large scale [19]. Nevertheless, the use of UAV-based systems in practice is limited by communication challenges, especially for transmitting gigabyte data.

Existing studies have indicated that the prevailing 4G network infrastructure is associated with considerable transmission delays (τ_1). These delays are major limitations for drone systems in facilitating real-time decision-making [5]. Consequently, interventions during critical periods in agriculture become impossible.

The introduction of 5G technology has been identified as a potential solution for overcoming the limitations associated with the prevailing 4G network infrastructure in facilitating real-time crop analysis. The high data rates and low latency associated with 5G technology are expected to overcome the transmission delays (τ_1), thereby enabling real-time crop analysis [10]; [17]. Nevertheless, there are considerable challenges associated with the implementation of 5G technology in agriculture. Firstly, the high deployment costs of the 5G network infrastructure and the unstable rural network coverage in attenuating signals in vegetation environments are critical limitations [21].

Therefore, although the technological possibilities of 5G-enabled UAV systems have been established, there remains a lack of quantitative evaluation of performance variability and operational risks in practical scenarios. In other words, most studies have concentrated on the average performance of UAV systems, without sufficiently addressing the effects of network instability on time-critical agricultural applications.

To bridge the gap, the objective of this study is to go beyond qualitative discussion and provide a quantitative feasibility study of a 5G-enabled UAV system. In other words, rather than concentrating on the average performance of a UAV system, as most studies have done, this research aims to model the variability in transmission latency and validate the system’s capacity to produce meaningful agricultural insights, using a technical artefact.

The rest of the paper is divided as follows: Section 2 outlines related studies on UAV systems, communication systems, and agricultural applications. Section 3 outlines the methodologies used, including latency modeling and artefact design. Section 4 outlines the results, including statistical analysis. Section 5 outlines strategic recommendations, based on the study, and Section 6 concludes the paper.

2 Related Works

Unmanned aerial vehicles (UAVs) have become essential tools for high-resolution environmental monitoring. [22] developed cost-effective drone monitoring toolkits for stream habitat health assessment. [23] introduced the Coastal Aerial Imagery Dataset for Shoreline Segmentation (CAID), emphasizing the importance of high-quality UAV imagery for geospatial analysis.

The system architecture for drone-enabled service has been studied by [10];[11];[12], who emphasized the importance of end-to-end reliability in UAV-based medicine logistics systems. [3] further proposed the integration of UAVs with IoT systems to improve scalability and robustness in smart environments.

[24] explored heterogeneous network architectures, demonstrating that combining multiple communication technologies can enhance system reliability in wide-area deployments. Recent studies have further investigated multi-layer and airground integrated networks to support UAV communications in complex environments [25].

Communication performance is another critical factor affecting UAV applications. [26] analyzed cellular-connected UAV systems and highlighted the challenges of interference management and coverage optimization. [15] examined the role of UAVs in wireless networks and emphasized the importance of latency and reliability in aerial communication systems.

With the development of next-generation networks, 5G has been widely recognized as a key enabler for UAV applications. [14] discussed the integration of UAVs into 5G networks, showing that high data rates and low latency can significantly improve system performance. [16] provided a comprehensive survey on UAV applications and communications, identifying reliability and scalability as major challenges.

However, communication performance in rural and complex environments remains a concern. [4] demonstrated that signal propagation for UAV communications is highly sensitive to environmental conditions, which can lead to unstable connectivity. Similarly, [2] showed that terrain and obstacles significantly affect air-to-ground channel characteristics, thereby impacting communication reliability.

3 Methodology

3.1 Quantitative Network Latency Modelling (τ1)

3.1.1 Governing Model.

Quantitatively measuring the performance of the network and focusing on speed consistency aim to help investment decisions. The amount of transmission payload is calculated based on a specific image file rather than a theoretical value to ensure maximum realism (Li, et al. 2025). The expected 50 photographs to be taken in a regular mission are multiplied by the size of a single image file to calculate the data volume in the simulation. The total task load calculated in this way is used as the input benchmark in the simulation scenario.

The main formula in this simulation model considers the relationship between the data transmission time and the volume of data transmitted effectively. This formula is similar to the standard telecommunication model used in the research on unmanned aerial vehicle telemetry [5]:

$$Ttransfer = (\text{Data Size})/(\text{Data Rate}) + Toverhead \quad (1)$$

Data Size: The Data Driven Payload is calculated by multiplying the test dataset's actual file size by the typical mission volume (50 pictures).

DataRate: The simulation scenario affects the network uplink speed (Mbps).

$T_{overhead}$: Real world network protocol overheads are represented by a latency factor, which is set at 5%.

3.1.2 Simulation Scenarios.

The methodology makes use of a scenario-based simulation to stress test the system in three different environments. To begin with, a 4G baseline is considered to act as a control to test efficiency gains with 5G deployment and to determine the initial bottleneck in the system. Next, a critical stress test is performed to analyze the volatile nature of edge coverage by using 100 iterations and standard deviation to statistically analyze risks pertaining to 5G deployment in rural areas.

3.2 Technical Artefact: Crop Health Analysis Model

In order to validate the analytical potential of the data, we created an image processing method. The method uses the green channel as a substitute for the near-infrared channel. This is a visible channel proxy method that has been shown to be capable of differentiating changes in biomass without the need for sophisticated multispectral equipment [8]; [18].

4 Key findings and analysis

4.1 Transmission Delay and Volatility Analysis

Assuming a total payload of 0.574GB, the simulation yielded the following re-sults:

Scenario	Average Transmission Time	Equivalent Minutes	Scenario
4G Baseline	1205 seconds	20.1 mins	4G Baseline
5G Typical	96 seconds	1.6 mins	5G Typical
5G Volatile (Mean)	61 seconds	1mins	5G Volatile (Mean)

Table 1:Transmission Performance Comparison

The findings confirm the significant average gain provided by 5G technology in comparison to the dominant 4G technology, as depicted in Table 1. The only limiting factor for the execution of real-time analytics under 4G technology is addressed; this is clearly demonstrated through the decrease in mean transmission times from nearly 20 minutes to approximately 1 minute (61 seconds).

However, a critical drawback of the system is revealed through the application of Stress Test Scenario 3: Volatile Edge Coverage. The most prominent result is the calculation of the standard deviation at 43 seconds. This significant fluctuation suggests that although the average task is relatively short in duration, a significant number of tasks will experience substantial peak delay times as a result of changes in signal strength within the edge coverage region.

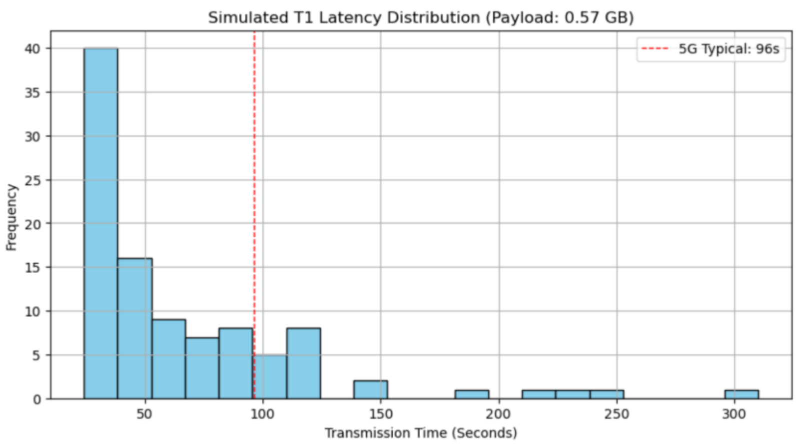

Figure1:A histogram illustrating the transmission time distribution in an unstable rural 5G network.

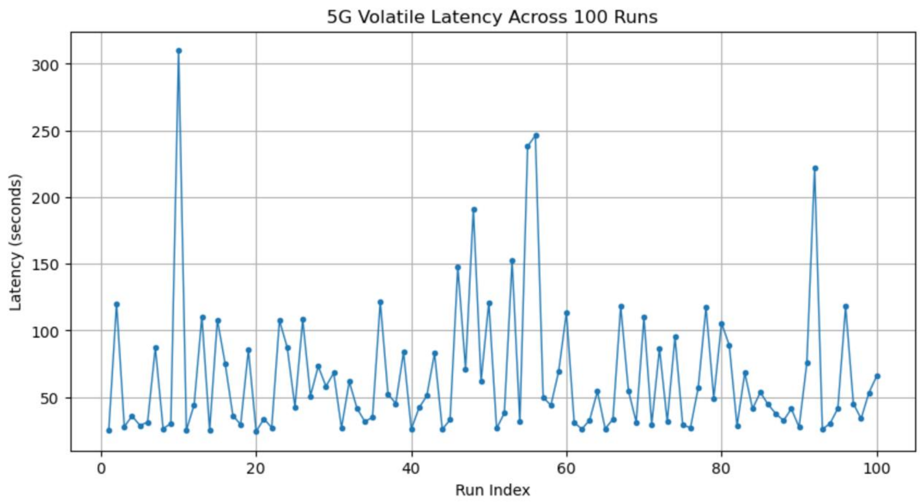

Figure2:Regarding the fluctuation graph of 100 simulation experiments

Run	Data Rate (Mbps)	Latency (s)	Latency (min)
1	189.78	25.41	0.42
2	40.12	120.19	2.00
3	172.91	27.88	0.46
4	134.58	35.83	0.60
5	167.07	28.86	0.48
6	154.86	31.13	0.52
7	55.36	87.09	1.45
8	182.93	26.36	0.44
9	160.06	30.12	0.50
10	15.55	310.00	5.17

Table 2: 100 Runs Detailed Results (first 10 rows)

The transmission times are not clustered around the mean value but are heavily skewed to larger values, i.e., they are not normally distributed. This is depicted in Figure 1 and 2. From a practical perspective, this suggests that a 5G standalone network is not likely to deliver the reliability required for a mission where a guaranteed upload in under two minutes is required to trigger an immediate irrigation response. This is in line with existing studies into mission-critical UAV and agri-IoT communications where it was found that latency variance was a more important limiting factor in mission success than throughput [7]; [20]. Therefore, a large and substantial risk exists where a critical intervention window in an agri-mission scenario is missed. The identified risk in the feasibility of operation was directly corroborated in this investigation. By converting the qualitative concern around “unstable rural coverage” into a quantitative measure (i.e., STD), a tangible measure was provided to inform strategic decisions.

From the simulation results(table 1and 2), it is clear that a considerable decrease in the average transmission times is achieved by shifting from the 4G network to the 5G network. However, apart from the average transmission times, the volatility of the transmission times becomes a key factor.

From the calculated standard deviation of around 43 seconds for the volatile 5G network scenario, it is clear that a high level of variability exists in the transmission times. This indicates that the network does not offer a stable performance level but rather a volatile performance level that depends on the environmental and coverage conditions.

From the histogram results, it is clear that the transmission times do not follow a normal distribution pattern but rather a right-skewed pattern, indicating a long tail effect. This indicates that a non-negligible percentage of the transmission times face severe levels of delay.

From a statistical perspective, the long tail effect indicates that the mean value does not provide a clear indication of the system's performance level. Although the mean transmission times fall within the acceptable limits, the possibility of severe levels of delay is high. This indicates that the mission-critical operations may not be performed due to the unpredictable levels of latency.

Step	Operation	Description
1	Data Input	Define dataset path (D), image count (N), and transmission rate (R)
2	File Search	Search image files matching pattern *_h*.jpg
3	Payload Initialization	If no image found, set payload (P = 1.0) GB
4	Payload Calculation	Select one image and compute total payload: (P = \frac{S \times N}{1024^3})
5	Overhead Setting	Set protocol overhead (o = 5%)
6	Simulation Loop	For each run (i = 1 \to K)
7	Rate Selection	If (R) is a range, sample (r_i \sim U(R_{min}, R_{max})); otherwise (r_i = R)
8	Unit Conversion	Convert rate to bps and payload to bits
9	Time Calculation	Compute (t_i = \frac{P_b}{r_i} \times (1 + o))
10	Data Storage	Store (t_i) into

		latency list (T)
11	Statistical Analysis	Compute mean (\mu) and standard deviation (\sigma)
12	Output	Return latency results and statistics

Table 3. Data Transmission Latency (T1) Simulation Procedure

In order to systematically describe the proposed methodology, the overall workflow can be broadly classified under two main categories: data transmission latency simulation and Modified NDVI analysis. Table 3 illustrates the procedure for the data transmission latency simulation model for T1. This model simulates the data transmission delay under various communication environments. The model initially estimates the data payload based on the given image dataset. It then simulates the data transmission delay under various data rates, both in stable and volatile environments for 5G communication. In addition to this, statistical measures are also derived to assess the system performance.

4.2 Technical Artefact Validation

In the image processing domain, a technical artefact of the computation process was created in the form of a Modified Normalised Difference Vegetation Index (MNDVI) calculation using the green channel of the RGB image as a substitute for the near-infrared channel to determine the analytical value of the system's result.

The system simulated a standard drone image frame through processing a sample RGB image (DJI_0093_h45.jpg), retrieved from a publicly accessible agricultural image dataset [1]. The MNDVI values were calculated and presented in the form of a heatmap (Figure 3), where the colorimetric scale represents healthy vegetation growth in deep green, moderate health/stress in yellow, and areas of concern in red that may indicate problems such as water stress, nutrient deficiencies, or diseases.

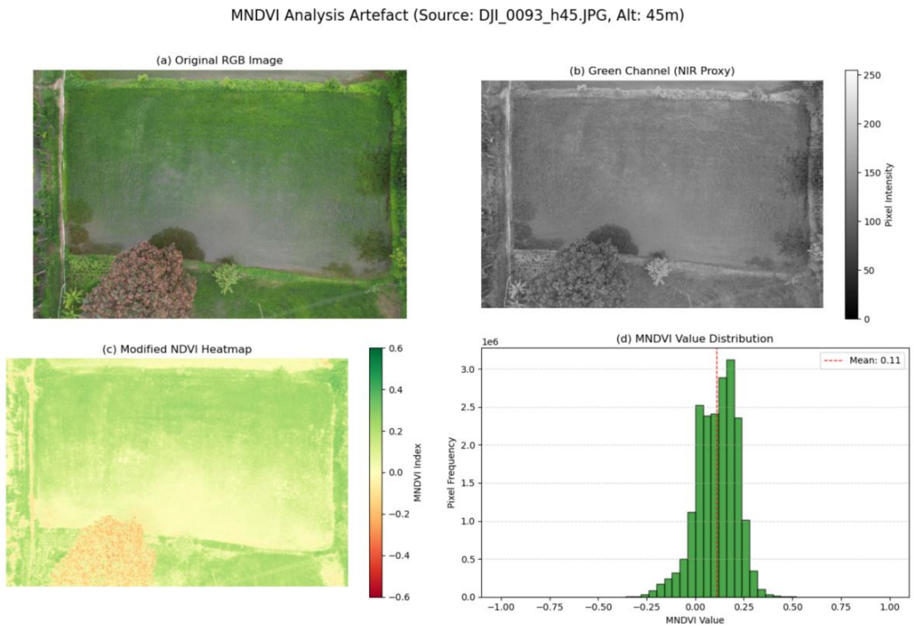

*Figure 3**:** MNDVI Proxy Heatmap (Technical Artefact Output).*

Step	Operation	Description

1	Image Input	Read RGB image (I)
2	Channel Extraction	Extract red channel (R) and green channel (G)
3	MNDVI Calculation	Compute (\text{MNDVI} = \frac{G - R}{G + R})
4	Value Cleaning	Replace NaN and infinite values with 0
5	Data Flattening	Convert MNDVI matrix into 1D vector (V)
6	Noise Filtering	Remove zero/background values from (V)
7	Statistical Analysis	Compute mean value (\mu_v)
8	Visualization	Generate RGB image, channel image, heatmap, histogram
9	Output	Return MNDVI map, distribution, and figures

Table 4. Modified NDVI (MNDVI) Image Analysis Procedure

Table 4 below illustrates the steps involved in the processing of the MNDVI analysis. This module focuses on retrieving significant information from the image data by determining an index related to vegetation through the use of the red and green channels. The process involves channel separation, index determination, data preprocessing, and statistical analysis, followed by visualization. The determination of the MNDVI heatmap and distribution provides a quantitative representation of the scene under observation.

5 Strategic Recommendations

In this section, it will be clear how the technical artefacts and quantitative models are linked to strategic suggestions that are data-driven. The results indicate that while the 5G technology decreases the average transmission latency ($\tau 1$), it simultaneously increases the quantified probability of instability in the rural region. Therefore, it is suggested that the adoption of the 5G drone system should be conditional on the demonstration of mitigating the unreliability of the 5G network.

5.1 Decision Context

In considering the integration of 5G-enabled drones in precision agriculture, the organization has been considering a wide range of strategic possibilities. These possibilities range from a direct leap into a pure 5G connectivity solution to a more measured approach involving a phased pilot program for high-value fields. At the more extreme end of the possibilities spectrum, the organization has also been considering the pros and cons of a delay in the maturity of rural infrastructure as a potential solution or even the complete rejection of the technology for this specific use case.

Recent modeling results, however, have essentially narrowed down these possibilities to a more limited set of choices by emphasizing the potential risks associated with both extremes of the possibilities spectrum. The "naive" approach of a direct leap into a pure 5G solution is essentially deemed not feasible due to the inherent volatility of the connection; in a critical process such as agriculture, even a short loss of signal equates to a significant level of risk. The complete rejection of 5G as a solution is also deemed not feasible due to the significant performance benefits that this technology has to offer.

5.2 Evidence Based Rationale

The results for quantitative measurements and artifacts show that the average $\tau 1$ transmission time is reduced from 1205 seconds to a range of 61 to 96 seconds. This shows a reduction in delay of over 90 percent, effectively removing the previous transmission bottleneck. However, the results also show that the rural 5G technology has a high standard deviation of approximately 43 seconds, confirming that in the case of severe latency spikes, there are risks to operational viability.

In the case of the technical artifact, the MNDVI heat map results show that the system effectively translates imagery into crop health. Moreover, the use of an RGB sensor with a proxy MNDVI approach ensures a cost advantage over the use of expensive multispectral equipment. Overall, the results show that the technology has quantifiable benefits and that the key risk area is the reliability of rural 5G technology rather than its speed. Viability concerns are also addressed by removing barriers to hardware investment.

5.3 Strategic Recommendation 1: Hybrid Network Architecture (5G + Local Mesh)

A hybrid network architecture is proposed to overcome the limitations identified in the previous section. In the proposed architecture, the 5G network is used for high-bandwidth data transmission, and a local low-bandwidth network is used for command and control. Empirical studies have shown that this type of heterogeneous network architecture is beneficial in enhancing the robustness and stability of the UAV communication links in wide-area remote areas. [3]; [24].

The proposed architecture ensures that each communication layer is used according to its capabilities. In the proposed system, the 5G network is used for high-bandwidth data transmission, and a local low-bandwidth network is used for command and control. This ensures the system is more robust to changes in cellular network coverage.

5.4 Strategic Recommendation 2: Drone-as-a-Service (DaaS) Business Model Recommendation

The 5G-enabled drone system can be commercialized as a Drone-as-a-Service (DaaS) subscription model, targeting high-value cash crops like vegetables and orchards instead of broad-acre crops with low profit margins. This strategy not only reduces the initial CapEx but also simplifies technical management, which is an effective strategy in scaling up IoT and drones in crisis response [6].
The organization can also deal with the issue of economic feasibility constraints through the use of cost-effective RGB payloads, which can deliver suitable intelligence at a lower system cost. The adoption of a Drone as a Service business model can also increase the accessibility of the technology to farmers with limited economic resources, given that it changes the cost structure from capital to operational costs. This model can be used to target segments with high return on investment

opportunities, especially in high value crops that require timely intervention in water management or disease control. In such cases, the 90 percent reduction in τ_1 and the MNDVI benefits can support premium pricing for real-time analytics.

Furthermore, the DaaS business model provides a way to scale from pilot to rollout. It provides the organization with the opportunity to test the hybrid solution in a limited and high-value client set to ensure real-world dependability before scaling the business. Ultimately, this business model brings the technology to life as it equates the performance benefits to the willingness to pay, eliminating the high investment hurdles associated with hardware assets.

6 Conclusion

The paper provides a quantitative evaluation of the performance of 5G-enabled drone systems in precision agriculture. The results show that the performance of 5G-enabled drone systems in transmission is significantly improved, allowing for near real-time data analysis.

However, the results also show that the variability in latency in rural environments remains a critical performance limitation. This has been revealed by the presence of long-tailed delay distributions.

A conditional adoption approach has been proposed to overcome these challenges. This approach has been achieved by considering the use of a hybrid network architecture and a service-oriented business model. Future work should expand this model to include edge computing processing on the drone or at the 5G edge in addition to service aggregation across multiple farms. Field empirical testing should also be conducted to validate the performance envelope and refine the simulation based on real-world conditions.

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