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Optimizing Inventory Management in Agro-Processing: Moving from Static Safety Buffers to Seasonal Dynamic Lead-Time Optimization

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Abstract - Agricultural inbound logistics operates in high-friction environments characterized by seasonal supply gluts, fragmented village aggregation points, and extreme stochastic lead-time variance. Conventional agro-processing enterprises frequently rely on rigid, transactional spot purchasing and static inventory policies—such as maintaining a flat 3-day buffer stock year-round—which lead to severe operational inefficiencies, capital lock-up, and factory stockouts. This study investigates the theoretical and empirical transition from static safety inventory models to an adaptive Dynamic Seasonal Safety Buffer Model.

By systematically analyzing empirical inbound data gathered across 180 truck shipments (3,600 metric tons total volume) during a 60-day agricultural harvesting cycle at Sarovar Nutrifert & Bio-Organics Pvt. Ltd., this research demonstrates how dynamically scaling reorder points and safety stocks across early, peak, and late harvest phases resolves supply chain friction. The findings indicate that transitioning to a dynamic safety buffering framework completely eliminates factory stockout downtime, reduces the average inventory holding footprint by 38.3% (lowering weighted average inventory from 300 MT to 185 MT), releases ₹34.50 Lakhs in blocked liquid working capital, and cuts warehouse biological spoilage by 71.1%.

Keywords - Agribusiness Supply Chain, Stochastic Lead Time, Dynamic Safety Buffers, Inventory Optimization, Agro-Processing Inbound Logistics.

1. INTRODUCTION AND BACKGROUND

1.1 Macro-Environmental Context of Indian Agribusiness

The Indian agribusiness and food processing sector serves as the vital economic conduit connecting decentralized rural farming communities to industrialized consumer markets. According to industry estimates, agriculture and allied sectors contribute approximately 18% to India's Gross Domestic Product (GDP) and employ over 45% of the national workforce. Despite its macroeconomic prominence, the upstream supply chain remains structurally fragmented. Raw agricultural produce typically transitions through multiple intermediaries—including village-level aggregators, local commission agents, wholesale Agricultural Produce Market Committee (APMC) mandis, and regional stockists—before finally arriving at central processing facilities. This multi-tiered channel structure introduces significant operational friction, information asymmetry, biological quality degradation, and high transaction costs.

For an agro-processing enterprise, this structure has a direct consequence: the factory does not buy from a single, predictable supplier but from a shifting web of aggregation points whose reliability changes with the crop calendar. Procurement planners must therefore treat inbound lead time not as a contractual constant but as a managed variable. Reviews of planning models in the agri-food supply chain stress that seasonality, perishability and yield uncertainty together set agri-food logistics apart from conventional manufacturing logistics (Ahumada & Villalobos, 2009), and that the performance of these chains has to be judged on efficiency, flexibility, responsiveness and product quality at the same time (Aramyan et al., 2007).

The processing plant, by contrast, is a fixed-capacity asset. Once commissioned, its conversion capacity, labour roster and utility costs are committed whether or not raw material is waiting on the dock. A line that stops for want of raw material continues to incur labour and overhead cost while producing nothing, and a line that is fully fed but surrounded by excess stock incurs storage, handling and spoilage cost instead. Inventory policy is therefore the main lever through which the enterprise balances these two costs, and the quality of that policy depends on how faithfully it reflects the variability of the inbound flow.

1.2 The Operational Dilemma: Static vs. Stochastic Inbound Flow

In standard discrete manufacturing environments, production demand is relatively stable, and component lead times exhibit low variance, allowing planners to utilize static safety stock policies (e.g., maintaining a fixed 3-day or 5-day buffer) with high reliability. However, in agro-processing enterprises, the

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inbound supply chain is governed by biological, seasonal, and environmental realities. While daily factory processing demand (D) remains strictly fixed by plant conversion capacity, inbound lead times (LT) are profoundly stochastic.

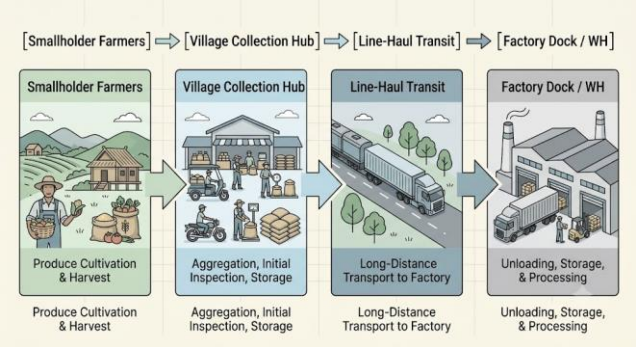


Fig. 1. Inbound agricultural supply chain: from smallholder farms through village collection hubs and line-haul transit to the factory dock and warehouse.

As harvesting seasons progress from early surplus to peak gluts and ultimately to late-season scarcity, rural aggregation networks experience severe bottlenecks. Village collection centers face labor shortages, transport vehicles experience non-standardized transit delays on unpaved rural roads, and processing plants suffer from weighbridge congestion. Maintaining a rigid, flat inventory buffer under these fluctuating conditions results in two major operational failures:

1. **Excessive Holding Costs During Gluts**: During peak harvesting phases, static buffers cause massive inventory accumulation, leading to high storage costs, physical congestion, and increased biological spoilage.
2. **Plant Starvation During Scarcity**: During late-season transitions, static buffers fail to absorb extended lead-time delays, resulting in chronic stockouts, unabsorbed factory labor, and costly production line downtime.

Two features make the problem harder than it first appears. First, the variability is not constant through the season: the same corridor, vehicles and collection centers behave differently in the first fortnight than in the last. A buffer calibrated to one phase is necessarily wrong for the others. Second, the two failure modes are not symmetric in their consequences. Excess stock is costly but recoverable, whereas a stockout stops production immediately and the lost hours cannot be recovered. Planners facing this asymmetry tend to inflate buffers across the whole season, which solves the stockout problem at the price of the holding-cost problem. The central question of this study is whether that trade-off can be broken by letting the buffer move with the risk.

1.3 Problem Statement

Many agro-processing firms inherit their inventory rules from general manufacturing practice or from the habits of the procurement team. A common rule is a flat buffer expressed in days of plant demand, such as three days of cover, applied from the first day of the harvest season to the last. Such a rule is easy to communicate, easy to audit, and easy to program into an enterprise resource planning (ERP) system. Its weakness is that it implicitly assumes the risk it protects against is the same in every week of the season. The empirical evidence examined in this paper indicates that it is not.

The problem addressed here can therefore be stated as follows: given a fixed plant consumption rate and an inbound lead time whose level and variability both change across harvest phases, how should the reorder point and safety buffer be set in each phase so that the plant is never starved, while the average stock held, the capital tied up in it, and the biological losses it suffers are kept as low as the evidence allows?

1.4 Research Objectives and Questions

The study pursues four objectives:

1. to characterize how the level and variability of inbound lead time change across the early, peak and late phases of a harvesting season;
2. to formulate a dynamic safety buffer and reorder point that scale with the phase-specific lead-time delay;
3. to benchmark the dynamic policy against a static three-day policy in terms of stockouts, inventory footprint, working capital and spoilage; and
4. to derive practical guidance for ERP configuration and procurement governance.

These objectives translate into three guiding questions. **RQ1**: Does inbound lead-time variance differ materially between harvest phases? **RQ2**: Can a simple phase-wise rule built on the maximum observed lead-time delay remove stockouts? **RQ3**: What is the effect of such a rule on average stock, working capital and spoilage relative to the static benchmark?

1.5 Purpose and Scope of the Study

This study addresses these operational vulnerabilities by evaluating the inbound supply chain of Sarovar Nutrifert & Bio-Organics Pvt. Ltd. The primary focus of this paper is to formulate, implement, and empirically validate a **Dynamic Seasonal Safety Buffer Model** that scales safety stock requirements in direct proportion to stochastic lead-time variance across distinct harvesting phases. The operational scope encompasses primary rural consolidation points (farm-gates and Village Collection Centers) through line-haul transit to the factory weighbridge, quality assurance laboratory, and raw material storage warehouse.

1.6 Significance and Structure of the Paper

The contribution of the paper is practical as much as theoretical. For practitioners, it shows that a three-parameter table—one safety buffer and one reorder point for each harvest phase—can replace a flat rule without any new technology, and it quantifies what the change is worth in stockouts avoided, storage released and capital freed. For researchers, it offers a documented case in which a classical worst-case cover rule is applied to a non-stationary, aggregation-driven inbound chain, together with a sensitivity analysis showing how robust the conclusions are to the main inputs.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on inventory theory, lead-time variability and agribusiness supply chain risk. Section 3 describes the research design, the lead-time decomposition and the phase segmentation. Section 4 develops the mathematical model, applies it to each phase and tests its robustness. Section 5 reports the comparative results. Section 6 discusses strategic implications and an implementation roadmap, Section 7 sets

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out limitations and future research directions, and Section 8 concludes.

2. COMPREHENSIVE LITERATURE REVIEW

2.1 Inventory Management and Stochastic Lead-Time Theory Under Uncertainty

The theoretical foundation of inventory management is rooted in balancing holding costs against stockout risks. Classical inventory models, extensively detailed by Chopra and Meindl (2016), establish that safety inventory acts as a mathematical cushion against demand and supply fluctuations. In their foundational work, Silver, Pyke, and Peterson (1998) formalize the calculation of reorder points (ROP) under conditions of uncertainty, demonstrating that safety stock must account for lead-time variability (σ_L) alongside demand variance (σ_D).

In the standard continuous-review treatment, the reorder point equals expected demand during lead time plus safety stock, and safety stock is set as a multiple of the standard deviation of demand during lead time, where the multiplier reflects the target cycle service level (Silver et al., 1998; Chopra & Meindl, 2016). When both demand and lead time are random, the variance of demand during lead time combines the two sources of uncertainty. Eppen and Martin (1988) show that procedures commonly used to combine them can give results far from those intended, and they present a correct alternative; their work underlines that lead-time variability deserves careful treatment in its own right rather than being folded into a demand-based rule of thumb. When demand is constant, as it is for a plant running at fixed capacity, the combined expression collapses so that all residual uncertainty is attributable to lead time.

However, standard economic order quantity (EOQ) and reorder point formulations assume that lead time is an independent, identically distributed random variable with low variance. When applied to agricultural raw materials, these assumptions break down. Agro-processing supply chains exhibit non-stationary lead-time distributions that shift dynamically across harvesting windows. Consequently, static safety stock policies inevitably produce system imbalances, manifesting as chronic stockouts during high-variance periods or excessive working capital lock-up during stable periods. The important point for this study is that the usual statement of the model treats the lead-time parameters as fixed numbers estimated once and applied throughout the planning horizon. If those numbers move with the harvest calendar, the policy must move with them.

2.2 Lead-Time Reduction and Supply Chain Responsiveness

Expanding on the mechanics of supply chain responsiveness, De Treville, Shapiro, and Hameri (2004) argue that managing and actively buffering against lead-time variability is significantly more critical for operational performance than merely inflating inventory buffers. In the context of agricultural supply chains, lead time is not a static parameter managed by a single vendor; it is a composite duration shaped by multiple sequential handoffs: order confirmation, farm-gate aggregation, primary rural transport, and factory dock offloading.

Failing to isolate these component lead times prevents management from identifying specific bottlenecks. De Treville et al. emphasize that operational agility requires adaptive inventory mechanisms that react in real-time or seasonally to lead-time stretching, thereby minimizing the Total Cost of Ownership (TCO).

Hopp and Spearman (2008) express a closely related idea in their treatment of variability in flow systems: variability that is not reduced at its source must be absorbed by one of three buffers—inventory, capacity or time—and every system pays for its variability in one of these currencies. For the agro-processor, plant capacity is fixed and waiting time for raw material is simply idle labor, so in practice inventory remains the buffer of choice. The policy question is then not whether to hold a buffer but how much to hold, and when.

2.3 Agribusiness Supply Chain Risks and Quantifiable Agility

Agribusiness supply chains possess unique physiological and economic characteristics that distinguish them from industrial manufacturing. Shukla and Jharkharia (2013) provide a comprehensive review of agri-fresh and semi-processed produce supply chains, highlighting the structural friction involved in managing biological raw materials where moisture content, foreign matter contamination, and post-harvest decay introduce severe quality risks. They note that traditional supply chain frameworks fail to account for the physical degradation of agricultural inventory over time.

Furthermore, Behzadi et al. (2018) review quantitative models in agribusiness supply chain risk management, emphasizing that stochastic modeling and scenario planning are mandatory for handling agricultural supply uncertainties, seasonal crop availability, and upstream transport volatility. Their findings corroborate the need for dynamic inventory policies that protect processing plants against supply shocks while mitigating warehouse holding losses.

The degradation of stock while it is held is the subject of the perishable-inventory literature. Nahmias (1982) reviews models in which items lose value or expire with age, so that the cost of holding stock includes a component that grows with the time spent in storage. For semi-perishable commodities such as grains and pulses the rate of loss is far slower than for fresh produce, but in humid warehouses it is not zero, and it accumulates in direct proportion to the time inventory is held. This is the mechanism by which an oversized buffer imposes costs that go beyond interest on capital.

2.4 Seasonality, Variability and the Case for Time-Varying Buffers

Fisher (1997) argues that a supply chain should be matched to the nature of the product it serves, with physically efficient chains for predictable products and responsive chains for products whose demand is uncertain. Although framed around demand, the logic extends naturally to supply: when the uncertainty sits on the inbound side, the buffer should sit there too, and it should move as the uncertainty moves.

The literature on the bullwhip effect points in the same direction. Lee, Padmanabhan, and Whang (1997) identify order batching, price fluctuation and rationing or shortage gaming among the causes of variability amplification upstream in a supply chain. Late-season competition among regional processors for a dwindling crop resembles the rationing behavior they

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describe: buyers who expect shortage inflate their requirements, which in turn makes the supplier's environment more volatile. A buffer policy that anticipates this phase, rather than reacting after the first stockout, is therefore well founded.

Textbook treatments of non-stationary demand recompute base-stock or reorder parameters period by period rather than fixing them once (Zipkin, 2000). The present study applies the same logic to non-stationary lead time, using the harvest phase as the planning period. The choice of phase rather than day as the unit of adjustment is deliberate: it keeps the policy simple enough for planners to administer while still capturing the major shifts in operating conditions.

2.5 Supply Chain Resilience and Risk Management

Christopher and Peck (2004) argue that resilience depends on visibility, flexibility and collaboration across the chain, and that firms should build resilience into the design of their supply networks rather than rely on emergency responses. Tang (2006) surveys approaches to supply chain risk management, including inventory-based, supply-base and flexibility strategies, and stresses the value of proactive measures against operational risks such as delay and disruption. In both accounts, a seasonal buffer schedule is a proactive measure: it is set in advance using known features of the crop calendar and observed lead-time behavior, and it does not wait for a disruption to reveal itself.

2.6 Summary of the Reviewed Literature

Table 1. Summary of reviewed sources and their relevance to this study

Source	Focus	Relevance to this study
Silver et al. (1998); Chopra & Meindl (2016)	Safety stock and reorder-point theory	Baseline model; assumes stationary lead time
Eppen & Martin (1988)	Safety stock under random lead time and demand	Care needed when lead time varies
De Treville et al. (2004)	Lead-time reduction and variability	Variability, not the mean, drives cost
Hopp & Spearman (2008)	Buffering of variability	Inventory as buffer when capacity is fixed
Zipkin (2000)	Foundations of inventory management	Period-by-period parameters for non-stationary conditions
Shukla & Jharkharia (2013)	Agri-fresh supply chains	Biological degradation of stock
Behzadi et al. (2018)	Agribusiness risk models	Need for stochastic, seasonal policies
Ahumada & Villalobos (2009)	Agri-food planning models	Seasonality and perishability
Aramyan et al. (2007)	Agri-food performance measurement	Multi-dimensional performance view
Nahmias (1982)	Perishable inventory	Holding cost grows with time in store
Fisher (1997); Lee et al. (1997)	Matching chain to product; bullwhip	Buffer placement; shortage gaming
Christopher & Peck (2004); Tang (2006)	Resilience and risk management	Proactive, calendar-based buffers

Summary prepared by the author from the sources cited in Sections 2.1–2.5.

Table 1 shows that the strands of literature are complementary rather than competing. Inventory theory supplies the buffering logic, the lead-time and variability literature explains why the buffer must respond to the spread of delivery times, and the agribusiness and resilience literatures explain why the response must be seasonal and proactive. What is missing is the combination of the three in a compact operating rule, which is the gap addressed next.

2.7 Research Gap

This study bridges the gap between theoretical inventory buffering and empirical agribusiness operations by demonstrating how a seasonally adaptive, dynamic safety buffer model can eliminate plant downtime, optimize warehouse footprints, and release trapped working capital in agro-processing inbound supply chains.

Three specific gaps motivate the work. First, classical safety-stock models treat lead-time parameters as stationary, which does not hold across a harvest season. Second, within the sources reviewed here, agribusiness risk studies concentrate on modeling frameworks and review-level guidance, and less on compact operating rules that a procurement planner can apply on the shop floor. Third, there is limited published evidence quantifying the stockout, capital and spoilage effects of seasonal buffer adjustment in aggregation-based procurement of the kind common in Indian agro-processing. The following sections address each gap in turn.

3. METHODOLOGY AND DATA FRAMEWORK

3.1 Research Design and Operational Scope

To evaluate the operational impact of lead-time variance and establish a robust empirical foundation for dynamic inventory buffering, this study adopted a quantitative observational research design. Empirical data was gathered over a rigorous 60-day operational window spanning the active agricultural harvesting season at Sarovar Nutrifert & Bio-Organics Pvt. Ltd. The dataset tracks a sample size of 180 inbound truck shipments, representing a cumulative raw material volume of 3,600 metric tons (MT) sourced across 12 regional Village Collection Centers (VCCs) and partnered Farmer Producer Organizations (FPOs).

The design is observational and comparative. It does not manipulate the supply chain; it records inbound shipments over a full harvest cycle, estimates phase-specific lead-time statistics, and uses those statistics to parameterize the buffer model. Policy outcomes under the static rule, based on the enterprise's historical performance, are then compared with outcomes under the dynamic rule. The unit of analysis is the inbound shipment; the 180 shipments and 3,600 MT in the sample imply an average consignment of 20 MT.

3.2 Lead-Time Decomposition Framework

To isolate the exact operational bottlenecks driving supply chain friction, total inbound lead time (LT_{total}) was decomposed into four sequential operational stages:

1. **Purchase Order Confirmation** (t_{order}): The duration from internal plant MRP generation to formal PO transmission and vendor acknowledgment.
2. **Farm Aggregation** ($t_{harvest}$): The time required for smallholders and Village-Level Aggregators (VLAs) to harvest, thresh, dry, bag, and consolidate produce at decentralized Village Collection Centers.

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3. **Line-Haul Transit** ($t_{transit}$): The physical transportation duration for 3-ton rural collection trucks and 10-to-20 ton line-haul carriers to travel from rural aggregation hubs to the central processing facility.
4. **Dock Quality Control & Weighbridge Processing** (t_{dock}): The time spent at the factory gate undergoing gross/tare weighbridge measurement, pneumatic core sampling, and laboratory quality assay testing.

$$LT_{total} = t_{order} + t_{harvest} + t_{transit} + t_{dock} \quad (1)$$

The sequence therefore runs from PO generation, through farm aggregation and line-haul transit, to dock quality control and weighing, as illustrated in Fig. 1. The decomposition matters because each stage responds to a different kind of intervention. Order confirmation delays are addressed by process and ERP automation; aggregation delays by coordination with VCCs and FPOs; transit delays by vehicle scheduling and route planning; and dock delays by weighbridge and laboratory capacity. This paper reports lead time at the aggregate level, so the stage-level split is presented as a framework for diagnosis and is left for more detailed future measurement.

3.3 Seasonal Harvest Categorization

To capture non-stationary operational dynamics, the 60-day sourcing window was segmented into three distinct harvesting phases:

- **Early Harvest (Days 1–15)**: Characterized by initial market arrivals, uncalibrated field collection workflows, and moderate supply availability.
- **Peak Harvest (Days 16–45)**: Marked by maximum volume gluts, intense farming activity, and severe downstream logistics congestion at factory receiving docks.
- **Late Harvest (Days 46–60)**: Defined by rapid crop exhaustion, widespread supply scarcity, extended aggregation times, and heightened competition among regional processors.

The early and late phases each span 15 days, or one quarter of the window, while the peak phase spans 30 days, or one half. Segmenting by phase rather than by calendar week keeps the policy simple enough for planners to administer: three parameter sets instead of sixty daily values. It also matches how procurement teams already talk about the season, which eases adoption.

3.4 Statistical Variance Tracking

Statistical deviation (σ_L) was computed for each harvesting phase to measure lead-time uncertainty. Empirical tracking revealed that lead-time variance escalated significantly as the season progressed, shifting from ±11.4 hours in the early harvest to ±24.2 hours in the late harvest. This escalating variance drove maximum observed lead times (LT_{max}) from an early baseline of 3 days up to 5 days during late-season shortages.

Table 2. Observed lead-time profile by harvest phase

Phase	Days	Avg. LT (days)	Avg. LT (hours)	Max. LT (days)
Early	1–15	2.0	48.9	3.0
Peak	16–45	2.0	47.1	4.0
Late	46–60	2.7	64.6	5.0

LT = inbound lead time. Values as reported by the study.

Three patterns stand out in Table 2. First, the maximum lead time rises by two thirds between the early and late phases (3 to 5 days), and the reported deviation more than doubles (11.4 to 24.2 hours, an increase of about 112%). Second, the average lead time rises by about 32% over the same interval in hours (48.9 to 64.6). Third, and most instructive, the average does not rise in the peak phase: at 47.1 hours it is slightly below the early-harvest figure of 48.9 hours, yet the maximum is a full day longer. Congestion at peak therefore shows up in the tail of the distribution, not in its center. A policy that is calibrated to average lead time would miss precisely the risk that matters.

3.5 Modeling Assumptions

The model developed in Section 4 rests on the following assumptions, which are stated explicitly so that readers can judge where the results do and do not transfer:

- Daily plant demand D is constant at 100 MT/day, fixed by processing capacity, so demand uncertainty is negligible relative to lead-time uncertainty.
- Within a phase, the lead-time statistics (average, maximum, deviation) are stable, and the phase boundaries are known in advance from the crop calendar.
- Replenishment is triggered when inventory reaches the reorder point for the current phase.
- Capital is valued at a flat ₹30,000 per MT, the average raw material valuation used in the study.
- The raw material is semi-perishable (grains and pulses), and spoilage is measured as a percentage of stored volume.
- The static benchmark is the enterprise's historical policy of a flat 300 MT buffer (three days of plant demand) held year-round.

3.6 Validity Considerations

Because the comparison is between the enterprise's historical performance under the static policy and its performance under the dynamic policy, differences in crop conditions, market arrivals or weather between the two periods could influence the outcomes independently of the policy itself. The results should therefore be read as strong operational evidence from one enterprise and one season, not as the output of a controlled experiment. Section 7 returns to this point and outlines how future work could strengthen causal attribution.

4. MATHEMATICAL MODEL AND DYNAMIC SAFETY BUFFER COMPUTATION

4.1 Theoretical Formulation of the Dynamic Buffer

Classical inventory management models safety stock as protection against demand uncertainty. However, in agro-processing operations, daily factory conversion demand (D) is held strictly constant by plant processing capacity (configured at 100 MT/day), whereas replenishment lead time (LT) is highly stochastic. When lead time fluctuates between average duration (LT_{avg}) and maximum observed duration (LT_{max}) due to rural aggregation and transit bottlenecks, the required safety buffer must absorb the maximum lead-time delay ($\Delta LT = LT_{max} - LT_{avg}$).

The mathematical formulation for the dynamic safety buffer is expressed as:

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$$SB = D \times (LT_{max} - LT_{avg}) \quad (2)$$

where SB is the safety buffer in MT. To maintain continuous factory feeding without holding excessive inventory during low-variance periods, the dynamic Reorder Point (ROP) is computed as:

$$\text{ROP} = D \cdot LT_{avg} + SB \quad (3)$$

Substituting Eq. (2) into Eq. (3) yields a useful identity. The average-lead-time terms cancel, leaving:

$$\text{ROP} = D \cdot LT_{max} \quad (4)$$

The dynamic reorder point is therefore the quantity of material the plant would consume during the longest lead time observed in the phase. The model is a worst-case cover rule: it guarantees that an order placed at the reorder point will not run the plant dry even if it arrives as late as the slowest delivery seen in that phase. The advantage of this formulation is its transparency. Every input is directly observable, and a planner can reproduce the calculation with a spreadsheet. Its main limitation, discussed in Section 7, is that the maximum is a single extreme observation and is therefore sensitive to outliers.

For comparison, the classical service-level formulation sets safety stock as a multiple of the standard deviation of lead-time demand. With constant demand, that deviation equals D times the lead-time deviation, giving:

$$SS = z \cdot D \cdot \sigma_L \quad (5)$$

where z is the standard normal deviate for the chosen service level. Section 4.4 uses Eq. (5) as an independent cross-check on the buffers produced by Eq. (2).

4.2 Phase-Wise Empirical Computations

Applying the dynamic safety buffer formulas to the empirical lead-yield data yields distinct operational inventory parameters across the three harvesting phases.

Early Harvest Phase (Days 1–15). Average lead time is 2.0 days (48.9 hours) and maximum lead time is 3.0 days (72.0 hours), so the lead-time delay is ΔLT = 1.0 day. The required safety buffer is 100 MT/day × 1.0 day = **100 MT**, and the dynamic reorder point is (100 × 2.0) + 100 = **300 MT**.

Peak Harvest Phase (Days 16–45). Average lead time is 2.0 days (47.1 hours) and maximum lead time is 4.0 days (96.0 hours), so ΔLT = 2.0 days. The required safety buffer is 100 MT/day × 2.0 days = **200 MT**, and the dynamic reorder point is (100 × 2.0) + 200 = **400 MT**.

Late Harvest Phase (Days 46–60). Average lead time is 2.7 days (64.6 hours) and maximum lead time is 5.0 days (120.0 hours), so ΔLT = 2.3 days. The required safety buffer is 100 MT/day × 2.3 days = **230 MT**, and the dynamic reorder point is (100 × 2.7) + 230 = **500 MT**.

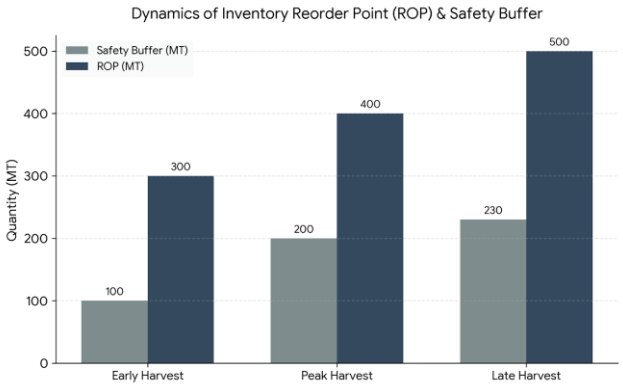


Fig. 2. Dynamics of inventory reorder point (ROP) and safety buffer by harvest phase. Quantities in MT.

Table 3. Dynamic safety buffer and reorder point by harvest phase

Phase	ΔLT (days)	Safety buffer (MT)	ROP (MT)	Capital in buffer (₹ Lakhs)
Early	1.0	**100**	**300**	30.00
Peak	2.0	**200**	**400**	60.00
Late	2.3	**230**	**500**	69.00

Capital in buffer = safety buffer × ₹30,000 per MT (the valuation used in the study).

Table 3 adds a financial reading of the buffers. At ₹30,000 per MT, each day of plant demand held as buffer (100 MT) ties up ₹30.00 Lakhs. The early-harvest buffer therefore carries ₹30.00 Lakhs, the peak buffer ₹60.00 Lakhs and the late buffer ₹69.00 Lakhs. The dynamic policy spends this capital only when the lead-time risk justifies it. The static policy, by contrast, carries a flat three-day cover (300 MT, ₹90.00 Lakhs) in every phase, regardless of how much delay risk the phase actually presents.

4.3 Reading the Model: Coverage Gaps of a Static Rule

Because Eq. (4) expresses the reorder point as the demand during the longest observed lead time, it also gives a direct measure of how well a static three-day trigger (300 MT) would have covered the worst case in each phase. The gap is simply the difference between the lead-time demand at LT_{max} and the static trigger.

Table 4. Worst-case coverage of a static three-day (300 MT) trigger

Phase	Demand over LT_{max} (MT)	Static trigger (MT)	Worst-case gap (MT)
Early	300	300	0
Peak	400	300	100
Late	500	300	**200**

Illustrative worst-case bounds computed from the study parameters; not observed outcomes.

Table 4 shows that the static rule is exactly sufficient in the early phase, where the longest lead time is three days, but leaves a worst-case shortfall of 100 MT (one day of production) in the peak phase and 200 MT (two days of production) in the late phase. These are upper bounds that materialize only when the slowest deliveries coincide with a depleted stock, so they do not predict how often a stockout will occur. They do, however, explain why the observed stockouts concentrated in the late harvest: that is where the static rule's exposure is largest. In the early phase the dynamic reorder point coincides with the static cover; the schedule departs from the flat rule only as the season's delay risk grows.

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A worked illustration makes the mechanics concrete. Suppose that in the late phase stock falls to 500 MT and an order is placed. If the delivery arrives after 2.7 days (the phase average), the plant has consumed 270 MT and still holds 230 MT, which is the safety buffer, when material arrives. If the delivery arrives after the maximum of 5.0 days, the plant has consumed 500 MT and stock reaches zero exactly as material arrives, with no production lost. Under a static 300 MT trigger, the same five-day delivery would leave the plant two days short, which corresponds to the unabsorbed labor and idle-line hours described in Section 5.2.

4.4 Cross-Check Against the Classical Service-Level Approach

As an independent test, the buffers from Eq. (2) can be compared with those given by Eq. (5), treating the reported ± values in Section 3.4 as one standard deviation of lead time. The peak-phase deviation is not reported in the study, so the comparison is made for the early and late phases only. Two common service levels are used: $z = 1.645$ (95%) and $z = 2.326$ (99%).

Table 5. Dynamic buffer versus classical service-level buffer

Phase	σ_L (h)	$D \cdot \sigma_L$ (MT)	$z = 1.645$ (MT)	$z = 2.326$ (MT)	Dynamic buffer (MT)
Early	11.4	47.5	78.1	110.5	**100**
Late	24.2	100.8	165.9	234.5	**230**

$D \cdot \sigma_L$ is computed with $D = 100$ MT/day and σ_L converted to days. Illustrative cross-check.

In the late phase the dynamic buffer of 230 MT sits almost exactly at the 99% service-level figure of 234.5 MT. In the early phase it lies between the 95% and 99% figures (78.1 and 110.5 MT). The two approaches are built from different statistics—one from the maximum, the other from the standard deviation—yet they point to similar buffer sizes. This agreement supports the reasonableness of the worst-case rule. Under the stated assumptions (deviation read as one standard deviation, approximately normal lead time), the dynamic buffer behaves like a high-service-level policy, giving roughly 95–99% protection in the two phases where both methods can be computed.

4.5 Sensitivity Analysis

The model has three inputs that a planner might doubt: the lead-time delay, the daily demand and the unit valuation of stock. Because the formulas are linear, their effects can be traced exactly.

Lead-time delay. From Eq. (2), each additional half-day of delay adds 50 MT of safety buffer, which at ₹30,000 per MT ties up ₹15.00 Lakhs. If the late-phase delay had been 2.8 days instead of 2.3, the buffer would be 280 MT rather than 230 MT. The buffer therefore scales one-for-one with the quality of the lead-time estimate, which argues for refreshing it at every harvest season.

Daily demand. Safety buffers scale proportionally with plant throughput. A ±10% change in D (90 or 110 MT/day) changes the early, peak and late buffers as shown in Table 6.

Table 6. Sensitivity of safety buffer (MT) to plant demand

Phase	$D = 90$	$D = 100$	$D = 110$
Early	90	100	110
Peak	180	200	220
Late	207	230	253

Safety buffer = $D \times \Delta LT$, with ΔLT of 1.0, 2.0 and 2.3 days.

Unit valuation. The capital released by the policy equals the reduction in average inventory (115 MT) times the price per MT. Table 7 shows how the capital figures change if the valuation is 10% lower or higher than ₹30,000.

Table 7. Sensitivity of working-capital effect to raw-material price (₹ Lakhs)

Price per MT	Static (300 MT)	Dynamic (185 MT)	Released
₹27,000	81.00	49.95	31.05
₹30,000	90.00	55.50	**34.50**
₹33,000	99.00	61.05	37.95

Computed from the study parameters; price levels are illustrative.

Even with a 10% fall in price the released capital remains above ₹31 Lakhs, so the conclusion about capital is robust to realistic price movements. The release also earns a recurring return. Applying illustrative annual cost-of-capital rates of 8%, 10% and 12% to the ₹34.50 Lakhs released gives indicative annual carrying-cost savings of about ₹2.76, ₹3.45 and ₹4.14 Lakhs respectively, before counting the avoided spoilage and stockout costs. The actual rate depends on the enterprise's financing mix and should be substituted by its finance team.

4.6 Extension: A Percentile-Based Variant

Because Eq. (4) anchors the reorder point to a single extreme observation, planners who prefer a less outlier-sensitive rule can replace the maximum with a high percentile of the phase's lead-time distribution. Writing LT_p for the p-th percentile (for example the 95th), the variant is:

$$SB^*_{p} = D \times (LT_{p} - LT^*_{avg}) \quad (6)$$

$$ROP^*_{p} = D \cdot LT_{avg} + SB^{***}_{p} \quad (7)$$

When $p = 100$ the variant reduces to the model used in this paper. Lower values of p trade a small, explicit risk of stockout for a smaller buffer, which allows management to price the protection it is buying. The variant has one practical requirement: percentile estimates are themselves noisy when a phase contains few shipments, so a minimum number of observations per phase should be agreed before the estimate is trusted, and the worst-case rule should remain the default until that threshold is met.

4.7 Sensitivity to Phase Boundaries

The phase boundaries in Section 3.3 are an input to the policy, so it is reasonable to ask how much the average inventory implied by the model depends on where they are drawn. Using the phase buffers of 100, 200 and 230 MT, the days-weighted average safety buffer under the 15/30/15 segmentation is $(15 \times 100 + 30 \times 200 + 15 \times 230) \div 60 = 182.5$ MT, within about 1.4% of the 185 MT weighted average inventory reported in Section 5.3. Table 8 shows how the figure moves if the boundaries shift.

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Table 8. Time-weighted average safety buffer under alternative phase lengths

Early / Peak / Late (days)	Average buffer (MT)	Capital (₹ Lakhs)	Change vs. 182.5 MT
15 / 30 / 15 (study)	182.5	54.75	—
15 / 25 / 20	185.0	55.50	+1.4%
10 / 30 / 20	193.3	58.00	+5.9%
20 / 30 / 10	171.7	51.50	−5.9%

Capital = average buffer × ₹30,000 per MT. Illustrative; phase lengths other than the study segmentation are hypothetical.

Even a five-day shift of days from one phase to another changes the average buffer by under 6%, and every alternative in Table 8 remains far below the static 300 MT. The policy is therefore not fragile with respect to the exact placement of the phase boundaries, which is reassuring for a procurement team that cannot know the crop calendar to the day. What matters more is that the late phase, with its higher buffer, is recognized before it starts.

5. RESULTS AND COMPARATIVE EMPIRICAL ANALYSIS

5.1 Benchmarking Static vs. Dynamic Inventory Policies

To measure the operational and financial efficacy of the proposed mathematical model, the historical performance of the enterprise under a traditional static inventory policy (maintaining a flat 300 MT buffer stock year-round) was directly benchmarked against the newly implemented dynamic seasonal safety buffer policy. Four outcome measures are examined: stockout incidents and associated downtime, average inventory footprint, blocked working capital, and in-storage spoilage.

5.2 Elimination of Factory Stockouts and Production Downtime

Under the legacy static policy, late-season lead-time spikes and aggregation bottlenecks stretched actual delivery times beyond the 3-day buffer threshold, resulting in **4 major stockout incidents** during the late harvest phase. These stockouts forced processing lines to halt operations, generating **38 operating hours of unabsorbed labor and factory idle downtime**. Transitioning to the dynamic seasonal buffer policy—which escalated safety stock to 230 MT during the late harvest—completely absorbed the 2.3-day lead-time delay, achieving **0 stockout incidents** and ensuring uninterrupted manufacturing continuity.

The location of the failures is itself informative. All four incidents fell in the late phase, which is the phase with the largest worst-case gap in Table 4 and the highest lead-time deviation in Table 2. This is consistent with the model's central claim that exposure to stockout risk is concentrated where lead-time variance is highest, and that a buffer allocated by phase protects the plant more effectively than one spread evenly across the season.

5.3 Inventory Footprint and Working Capital Optimization

Holding a rigid, maximum-capacity buffer year-round under the static policy locked up excessive warehouse space and financial capital. By aligning inventory holding levels with actual seasonal variance rather than maintaining a static cushion, the weighted average inventory holding footprint dropped from 300 MT down to 185 MT, representing a massive **38.3% reduction in average inventory storage**.

Priced at an average raw material valuation of ₹30,000 per MT, this reduction in holding volume successfully lowered blocked capital from ₹90.00 Lakhs down to ₹55.50 Lakhs. Consequently, the dynamic inventory policy permanently released **₹34.50 Lakhs in liquid working capital**, which was redirected toward core business expansion and farmer partnership programs.

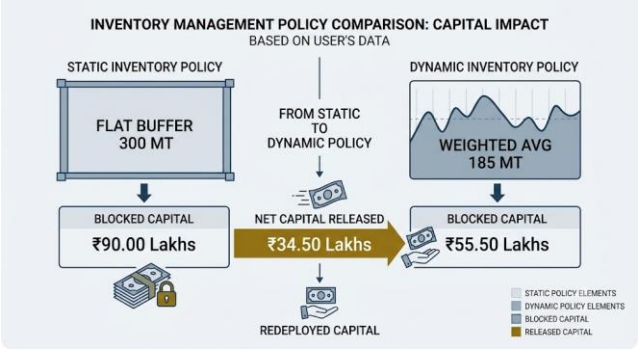


Fig. 3. Capital impact of the static policy (flat 300 MT buffer, ₹90.00 Lakhs blocked) versus the dynamic policy (185 MT weighted average, ₹55.50 Lakhs blocked), releasing ₹34.50 Lakhs.

The released capital has a strategic as well as a financial value. In agro-processing, working capital is often the binding constraint at exactly the moment procurement is most intense, because farmers and aggregators expect prompt payment at the peak of the season. Freed capital can be used to pay partners faster, to secure supply in tight periods, or to finance capacity upgrades, all of which reinforce the reliability of the inbound chain that the buffer is designed to protect.

5.4 Mitigation of Warehouse Biological Spoilage

Excessive inventory holding periods in humid warehouse environments accelerate biological degradation and insect infestation in agricultural grains and pulses. By maintaining a leaner, faster-moving inventory profile under the dynamic policy, the enterprise successfully reduced in-storage biological spoilage from **3.8%** of stored volume down to **1.1%**, marking a **71.1% reduction in warehouse holding losses**.

A simple flow relationship helps interpret this result. When throughput is fixed, average inventory equals throughput multiplied by the average time material spends in stock (Little's law). At 100 MT/day, an average inventory of 300 MT corresponds to about 3.0 days of cover, while 185 MT corresponds to about 1.85 days. The dynamic policy therefore shortened the average residence time of stock by the same 38.3% by which it reduced the footprint. Because biological degradation grows with time in storage (Nahmias, 1982), a shorter average residence time is consistent with the observed fall in spoilage, although this study does not isolate other contributing factors such as storage conditions or lot quality.

5.5 Consolidated Performance Comparison

Table 9. Consolidated comparison of static and dynamic policies

Indicator	Static	Dynamic	Change
Stockout incidents (late harvest)	4	0	−100%

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Indicator	Static	Dynamic	Change
Idle / unabsorbed labor hours	38 h	0 h	Eliminated
Weighted average inventory (MT)	300	185	−38.3%
Average days of cover*	3.00	1.85	−38.3%
Blocked capital (₹ Lakhs)	90.00	55.50	−₹34.50 L
In-storage spoilage (% of stored volume)	3.8%	1.1%	−71.1%

**Derived: average inventory ÷ 100 MT/day. Other values as reported by the study.*

Table 9 collects the principal results. The dynamic policy improves all four dimensions at once, which is notable because inventory policies usually trade one against another: a larger buffer reduces stockouts but raises holding cost and spoilage. The explanation lies in how the buffer is allocated. Instead of carrying a uniform cushion that is too thick in some phases and too thin in others, the dynamic policy redistributes the same protective logic across the season so that the stock is held when and where the delay risk is real.

5.6 Cost-Benefit Considerations

The benefits reported above must be set against the costs of adopting the policy. Those costs are modest and mostly organizational. They consist of the analyst time needed to estimate phase parameters, the effort of configuring the ERP calendar and parameter table, and the discipline of the review at each phase boundary. No capital equipment is required, and no change to physical storage is needed. The dynamic policy does carry a larger buffer in the late phase than in the early phase—130 MT more, equal to ₹39.00 Lakhs at the stated valuation—but this increment is deliberate and is more than offset, over the season as a whole, by the lower weighted average.

On the benefit side, the study documents four distinct items: 38 hours of idle production avoided, ₹34.50 Lakhs of capital released, a 38.3% smaller storage footprint, and a spoilage rate cut from 3.8% to 1.1% of stored volume. Because the policy requires no capital outlay, the payback is effectively immediate, and the main risk is not cost but complacency: if parameters are not refreshed each season, the policy will gradually revert to a stale flat rule.

6. DISCUSSION AND STRATEGIC IMPLICATIONS

6.1 Re-engineering Agribusiness Supply Chain Strategy

The empirical findings of this study challenge the uncritical adoption of manufacturing inventory theories in agribusiness. Because agricultural supply chains are subject to biological cycles, weather shocks, and fragmented rural infrastructures, static inventory policies are inherently flawed. Supply chain managers in agro-processing enterprises must recognize that lead-time variance is not an exogenous nuisance to be absorbed by brute-force inventory inflation; rather, it is a quantifiable operational parameter that must be managed through dynamic, phase-aware mathematical modeling.

This conclusion is consistent with the broader literature. De Treville et al. (2004) argue that variability in lead time, rather than its average, drives operational penalties, and the observation in Section 3.4 that peak-phase congestion appears in the tail rather than the mean of lead time supports that view. Hopp and Spearman (2008) frame inventory as one of three possible buffers against variability. The results here indicate that, when plant capacity is fixed and idle time is expensive, inventory is the right buffer, but only if its size is tied to the variability it is meant to absorb.

6.2 Why a Phase-Aware Buffer Outperforms a Flat One

The flat buffer fails for a structural reason. It is a single number chosen to cover the worst phase, or a compromise that covers no phase well. If it is set high enough for the late harvest, it overstocks in the early phase by two days of demand; if it is set for the early phase, it leaves the plant exposed in the late phase. No single value can be right across phases whose delay risk ranges from one day to more than two. A phase-aware schedule removes this dilemma by allowing the cushion to rise and fall with the risk.

There is also a behavioral advantage. A flat rule gives planners no signal when conditions change, so they respond to the first stockout by raising the buffer permanently, and it is rarely lowered afterward. A phase table builds the expectation of change into the policy itself: planners know in advance that the buffer will rise at the start of the peak phase and again in the late phase, and can plan storage, financing and supplier engagement accordingly.

6.3 Integration with Enterprise Resource Planning (ERP) Systems

For these dynamic models to scale beyond single-season pilot projects, organizations must institutionalize automated ERP reorder alerts. By programming ERP systems to automatically adjust reorder points (ROP) and safety stock thresholds as harvesting calendars transition from early to peak and late phases, companies can eliminate human error, reduce administrative overhead, and ensure seamless coordination between field procurement officers and central warehouse planners.

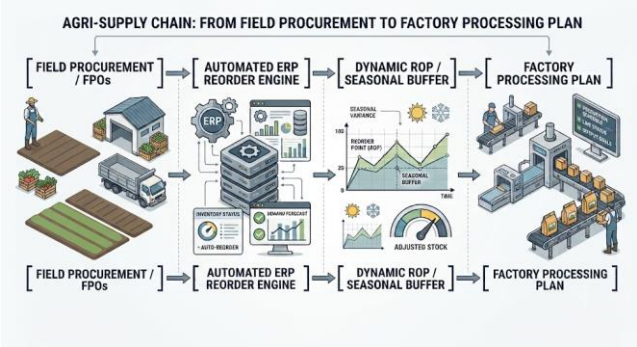


Fig. 4. Proposed flow from field procurement and FPOs, through an automated ERP reorder engine and dynamic ROP / seasonal buffer, to the factory processing plan.

In practical terms the ERP configuration is modest. It requires a calendar table that maps dates to harvest phases, a parameter table holding the safety buffer and reorder point for each phase, and a rule that applies the parameters of the current phase when the system evaluates stock against the reorder point. Because the phase table is the only moving part, it can be reviewed and signed off by procurement, finance and operations together before each season, which provides a natural governance checkpoint.

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6.4 Implementation Roadmap

The transition from a static to a dynamic policy can be staged to limit risk. Table 10 outlines a five-step roadmap that the enterprise, or a similar processor, could follow.

Table 10. Implementation roadmap for a dynamic seasonal buffer

Step	Activity	Outcome
1	Define phases	Agree harvest-phase boundaries from the crop calendar and prior-season arrivals.
2	Capture lead times	Record shipment-level timestamps for each of the four lead-time stages.
3	Set parameters	Compute LT_{avg}, LT_{max}, safety buffer and ROP for each phase using Eqs. (2)–(3).
4	Configure ERP	Load phase calendar and parameter table; enable automatic reorder alerts.
5	Review and refine	Compare outcomes with targets after each phase; update parameters before the next season.

Roles: procurement, warehouse, finance and IT/ERP teams jointly own steps 1–5.

6.5 Procurement and Supplier-Side Implications

The buffer model takes lead time as given, but lead time is partly under the enterprise's influence, and procurement practice can complement the inventory policy. Closer coordination with Village Collection Centers and Farmer Producer Organizations can shorten the aggregation stage, for example through advance commitments in the early phase when supply is plentiful and pickups can be scheduled in batches. Staggering truck arrivals reduces queues at the weighbridge during the peak phase, where dock congestion is most severe. Laboratory capacity at the dock can be planned in line with the peak arrival schedule so that quality assays do not become the binding stage.

These measures act on the numerator of the buffer formula. Every day removed from the maximum lead time reduces the late-phase safety buffer by 100 MT and releases ₹30.00 Lakhs of capital at the stated valuation. Inventory policy and supplier development are therefore complements rather than substitutes: the first protects the plant against delay that already exists, and the second reduces the delay that has to be protected against.

6.6 Monitoring and Governance

A dynamic policy is only as good as the feedback that maintains it. A small set of indicators, reviewed at each phase boundary, is sufficient to keep it calibrated:

- **Service indicators**: stockout incidents and idle production hours, tracked against a target of zero.
- **Lead-time indicators**: average, maximum and deviation of lead time by phase, compared with the values used to set the buffer.
- **Inventory indicators**: average stock and days of cover against the phase reorder point.
- **Financial and quality indicators**: capital blocked in raw material and spoilage as a percentage of stored volume.

If observed lead-time maxima exceed the values built into the table, the buffer should be revised upward before the next phase; if they fall consistently below it, the buffer can be reduced. Assigning one owner to this review, and recording each revision with its rationale, prevents the parameters from drifting back to an informal flat rule.

6.7 Positioning Against Prior Work

Relative to the classical approach in Silver et al. (1998), the contribution here is not a new formula but a re-parameterization: the same safety-stock logic, applied with lead-time statistics that are allowed to change by phase. Relative to the agribusiness risk literature (Behzadi et al., 2018; Shukla & Jharkharia, 2013), the contribution is an operating rule simple enough to be implemented without optimization software, together with an empirical estimate of its effects. Relative to resilience frameworks (Christopher & Peck, 2004; Tang, 2006), it offers one concrete, measurable instance of building resilience in advance rather than responding after a disruption.

6.8 Change Management and Adoption

Technical correctness is not sufficient for adoption. Procurement officers who have lived through stockouts tend to distrust any proposal that lowers a buffer, and warehouse managers who have managed overflowing stores tend to distrust any proposal that raises one. Three practices ease the transition. First, present the phase table as an agreed, jointly owned plan rather than as an analyst's output, with procurement, warehouse, finance and operations all signing it off. Second, define in advance a small set of conditions under which planners may override the table—for instance, a confirmed transport strike or a weather event—and require overrides to be logged. Third, share the results of each phase openly, including cases where the buffer proved too high or too low, so that the table is treated as a living instrument that improves with evidence rather than as a rule to be defended.

7. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

7.1 Limitations

Several limitations qualify the findings and should be kept in view when applying them elsewhere.

- **Single enterprise and single season.** The data cover 180 shipments over one 60-day cycle at one company. Lead-time behavior in other regions, crops or seasons may differ, and the phase boundaries and parameters would need to be re-estimated.
- **Before-and-after comparison.** The static and dynamic policies are compared across periods rather than through a controlled experiment, so differences in crop conditions or market arrivals cannot be fully excluded as contributing factors (Section 3.6).
- **Reliance on the maximum.** Eq. (4) shows that the reorder point is anchored to the longest observed lead time in a phase. A single extreme delivery can inflate the buffer, and a phase without extreme deliveries can understate the risk of the next one. Percentile-based or distribution-based estimates would be more stable.
- **Constant demand and flat valuation.** The model assumes fixed plant throughput and a uniform ₹30,000 per MT valuation. Section 4.5 shows that the conclusions are robust to ±10% variation in these inputs, but larger swings in price or throughput would require re-estimation.

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- **Aggregate lead time.** Lead time is analyzed in aggregate, so the contribution of each of the four stages to the observed variance is not separately quantified.

7.2 Future Scope of Work

While this study successfully models dynamic inventory buffering across a 60-day agricultural harvesting cycle, several avenues remain open for future academic and applied research:

- **Predictive Analytics and Machine Learning**: Future optimizations should focus on integrating machine learning forecasting algorithms and satellite Normalized Difference Vegetation Index (NDVI) crop health data to proactively forecast farm-gate arrival volumes and yield quality before harvests begin.
- **Cold-Chain Integration**: The current mathematical models assume semi-perishable grains and pulses; extending this framework to highly perishable horticultural crops (such as berries, fruits, and leafy greens) will require incorporating thermal degradation variables and refrigerated transit tracking into the inventory matrix.
- **Sustainable Green Logistics**: As regional sourcing networks expand, future studies should evaluate the feasibility of deploying battery-electric commercial trucks (e-LCVs) for short-radius rural aggregation milk-runs to lower carbon emissions and align with corporate sustainability mandates.
- **Multi-Season and Multi-Site Validation**: Repeating the study over several harvest seasons and at several plants would test whether the phase structure and the parameters are stable, and would allow formal statistical comparison between policies.
- **Probabilistic Service-Level Formulation**: Replacing the worst-case rule with a percentile or service-level rule, parameterized from the full lead-time distribution, would make the trade-off between protection and holding cost explicit and tunable.
- **Stage-Level Lead-Time Analysis**: Measuring each of the four lead-time stages separately would show which stage drives late-season variance and where supplier or dock investments would yield the largest reduction in buffer requirements.
- **Joint Optimization with Price and Storage Costs**: Extending the model to include price volatility, storage capacity constraints and financing costs would allow buffer sizing to be optimized against total cost rather than service alone.

8. CONCLUSION

Agricultural inbound logistics inherently operates in an environment of high stochastic friction, where lead times fluctuate due to rural aggregation bottlenecks, transit delays, and processing plant queues. This study demonstrates that traditional, rigid inventory policies—such as maintaining a flat, static safety buffer year-round—are structurally inadequate for managing seasonal harvesting cycles.

By replacing static inventories with a **Dynamic Seasonal Safety Buffer Model** that scales safety stock from 100 MT in the early harvest to 230 MT in the late harvest, agro-processing enterprises can effectively absorb lead-time variance (σ_L) without inflating inventory holding costs. Empirical validation across 180 shipments proves that aligning inventory reorder points (ROP) with seasonal lead-time behavior entirely eliminates factory stockout downtime, reduces the average inventory holding footprint by **38.3%** (from 300 MT to 185 MT), releases **₹34.50 Lakhs** in blocked working capital, and cuts warehouse spoilage by **71.1%**.

Three lessons follow for practice. First, the average lead time is a poor guide to risk; the tail of the distribution, which widens as the season advances, is what stops production. Second, the policy that responds to this is simple—a three-row table of phase-specific buffers and reorder points—and can be administered in a spreadsheet or an ERP parameter table with no new technology. Third, the benefits are not limited to service: the same schedule shortens the average residence time of stock, frees working capital and reduces biological losses, so that protection of the plant and efficiency of the warehouse are pursued together instead of traded against each other.

The sensitivity analysis shows that these conclusions are robust to moderate changes in demand and price, and the cross-check against a classical service-level formulation suggests that the dynamic buffer provides protection broadly in line with a high service level. At the same time, the evidence comes from one enterprise and one season. Replication across seasons, sites and crops, together with a probabilistic refinement of the worst-case rule, is the natural next step. Until then, the study offers agro-processors a practical, quantified and transparent alternative to the flat buffer: let the cushion rise and fall with the risk.

APPENDIX A. NOTATION AND ABBREVIATIONS

Table 11. Symbols and abbreviations used in the paper

Symbol / term	Meaning
D	Daily plant processing demand, fixed by capacity (100 MT/day)
LT	Inbound lead time from order to availability at the factory
LT_{avg}, LT_{max}	Average and maximum observed lead time within a harvest phase
ΔLT	Lead-time delay, $LT_{max} - LT_{avg}$
σ_L	Standard deviation (reported deviation) of lead time
SB	Dynamic safety buffer in MT
ROP	Reorder point: stock level at which a replenishment order is triggered
z	Standard normal deviate for a chosen service level
MT	Metric ton
₹ Lakh	Rupees one hundred thousand
VCC / FPO / VLA	Village Collection Center / Farmer Producer Organization / Village-Level Aggregator
APMC	Agricultural Produce Market Committee
ERP / MRP / PO	Enterprise resource planning / material requirements planning / purchase order
TCO	Total Cost of Ownership

APPENDIX B. PLANNER'S WORKSHEET

The calculation in Section 4 can be reproduced in a spreadsheet with the layout in Table 12. Each row of the phase table holds the inputs; the safety buffer and reorder point are computed from them, and the final check confirms the identity in Eq. (4).

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Table 12. Suggested worksheet layout for the phase parameter table

Field	Source or formula	Example (late phase)
Phase and dates	Crop calendar	Late, days 46–60
D (MT/day)	Plant capacity	100
LT_{avg} (days)	Mean of shipment lead times in the phase	2.7
LT_{max} (days)	Longest shipment lead time in the phase	5.0
ΔLT (days)	$LT_{max} - LT_{avg}$	2.3
Safety buffer (MT)	$D \times \Delta LT$	230
ROP (MT)	$D \times LT_{avg}$ + buffer	500
Check	ROP = $D \times LT_{max}$	100 × 5.0 = 500

Example values are those reported by the study for the late harvest phase.

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