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Synergizing IoT and Multi-Agent Systems A Decision-Support Framework for Weather-Resilient Cotton Farming

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Abstract - Cotton decision support has moved from isolated forecasts toward coordinated, agent-driven operations. The earlier body of work contributed interpretable weather-based risk estimation, degree-day phenology, microclimate correction, and ontology-backed advisory systems for whitefly, jassid, thrips, and pink bollworm [7]–[23], [26]–[33], [39]–[46], [51], [52]. More recent studies extend this foundation through multi-agent irrigation scheduling, mission planning for field operations, IoT-based monitoring, and learning-assisted control of water and other inputs [53]–[62]. Taken together, these streams point to a practical architecture for cotton farming: transparent weather and crop-stage signals, a knowledge layer that keeps recommendations legible, agent controllers that coordinate resources, and delivery pipelines that remain reliable under real field conditions. This review synthesizes those strands and organizes the evidence into a practical operational framework covering signals and features, knowledge and ontology, sensing and machine learning, agent-based resource optimization, delivery architecture, and deployment governance.. The review shows that the most reliable systems combine transparent weather baselines, careful data validation, explicit thresholds, and safe fallback behavior when sensors drift, weather falls outside the training range, or connectivity drops.

Keywords: **Cotton farming; decision support systems; intelligent agent systems; multi-agent systems; Internet of Things; weather-driven pest forecasting; ontology-based advisory; irrigation optimization**

1. INTRODUCTION

Cotton production remains highly sensitive to pest pressure, irrigation timing, and the quality of field decisions made under uncertainty. Weather, crop stage, and local management history interact over short horizons, making the difference between a timely intervention and a preventable loss. This is why decision support in cotton has evolved around short-lead forecasting, local advisories, and threshold-based actions rather than broad seasonal intuition alone [7]–[23]. Work on residues, climate-linked pesticide demand, and integrated pest management has further reinforced the need for targeted, explainable interventions instead of fixed calendar spraying [1]–[6].

The cotton literature already provides a strong operational base. Degree-day rules and lagged weather features offer biologically grounded explanations of pest development [7], [21]. Hurdle and zero-inflated regressions handle sparse trap and scouting counts while preserving interpretability [19], [20], [22]. Ontology-backed and expert-system approaches translate predictions into clear, label-safe actions that extension teams can audit and update [34], [39]–[46]. At the same time, low-cost sensing, phone-based imaging, and mobile advisory platforms have made field-scale data capture more practical [16], [17], [26], [27], [49], [50].

The newer agent and IoT literature extends this core in an important way. Rather than simply predicting risk, agent-based systems coordinate resources such as irrigation, field missions, edge computing, and alerts across multiple plots and devices [53]–[62]. The decision problem therefore extends beyond weekly risk estimation to field prioritization, resource allocation, and system response under changing weather, network quality, and sensor reliability. The novelty of this review lies in connecting cotton-specific forewarning and ontology-based DSS literature with the newer agent and IoT literature on operational resource coordination, rather than treating them as separate strands.

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2. SCOPE AND METHODS

This study is a targeted narrative review based on two manually curated literature sets: cotton pest and DSS studies, and agent-based resource optimization studies relevant to smart agriculture. The first consists of 52 unique cotton and decision-support studies after de-duplication. These papers and reports cover weather-driven forewarning, microclimate-aware pest management, imaging and sensing, ontology and expert systems, yield-linked modeling, and advisory delivery. The second corpus consists of 10 newly added papers on intelligent agents, IoT delivery, mission planning, fuzzy cognitive maps, irrigation management, and smart agriculture control [53]–[62].

The reviewed studies were grouped into six functional layers: signals and features, interpretable baselines, knowledge and ontology, sensing and machine learning, agent control and scheduling, and delivery and governance. For each paper, the following fields were considered wherever available: target problem, crop or farm context, inputs, feature engineering, model or controller family, validation design, reported outcomes, deployment notes, and operational constraints. Because the studies vary substantially in design, metrics, and maturity, the review uses a structured narrative rather than a statistical meta-analysis. Emphasis is placed on deployment credibility, especially year-wise or site-wise validation, bias correction, reason codes, and maintenance requirements. Studies were retained when they addressed cotton forewarning, cotton-relevant decision support, ontology-based advisory or agent-driven optimization of agricultural resources such as water, sensing, or field operations.

3. WEATHER-DRIVEN FOREWARNING

Weather-driven models remain the most practical starting point for operational cotton DSS. Weekly summaries of temperature, relative humidity, rainfall, wind, and short lag structures appear repeatedly across successful studies [7]–[23]. These models are useful because they align with pest biology and can be explained to non-specialist users. Whitefly incidence forecasting in Punjab and Tamil Nadu illustrates how local calibration converts generic weather relationships into district-level advisories with useful one- to two-week lead times [19], [20]. Temperature-based phenology offers similarly clear value for pink bollworm by linking control windows to thermal accumulation rather than intuition [21].

Where trap counts and field observations are sparse or zero-heavy, hurdle and zero-inflated approaches are especially valuable. They address the statistical reality of low-count pest data without collapsing into unstable estimates [22]. That matters in practice because cotton monitoring is irregular, station coverage is imperfect, and false certainty is dangerous. More classical GLM and GLMM approaches still have value where counts are moderate and variance is manageable [9], [11], but many operational datasets favor models that explicitly account for zero inflation.

These weather-driven systems perform best when paired with stable field data practices, including reliable station placement, crop-stage logging, and consistent scouting. Nearby or bias-corrected stations, crop-stage logs, and limited but consistent scouting outperform high-complexity models fed by noisy data. This is the underlying lesson across much of the cotton forecasting literature: strong operations beat flashy modeling when the goal is a usable farm system. The main model families represented in the literature differ less in mathematical sophistication than in their data requirements, maintenance burden, and failure behavior under field conditions.

Table 1. Model families and trade-offs

Model family	Typical use	Strengths	Limits	Data needs	Validation to require	Refs
Degree-day rules (phenology thresholds)	Stage-timed actions, e.g., PBW	Simple, transparent; easy to maintain	Needs local calibration; sensitive to sowing date errors	Daily Tmax/Tmin near fields; sowing dates	Year-wise or site-wise splits; threshold checks	[7], [21]
Hurdle / Zero-inflated (ZINB) counts	Sucking pests with many zeros	Handles zero inflation; interpretable coefficients	Can overreact to station gaps; lag mis-spec hurts	Weekly weather with 1–3 week lags; trap counts	Site-wise CV; zero-fraction sensitivity	[19], [20], [22]
GLM/GLMM counts	Incidence where variance is moderate	Coefficients readable; quick to fit	Less robust to heavy zeros	Weekly weather; stage flags	Site-wise CV; dispersion checks	[9], [11]
Time-series ML	Nonlinear interactions;	Captures	Needs drift	Multi-year weather;	Rolling-origin	[23],

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Model family	Typical use	Strengths	Limits	Data needs	Validation to require	Refs
(trees, LSTM/GRU)	longer lags	interactions; can improve lead	monitoring; risk of overfit	stage markers; labels	eval; out-of-sample districts	[27], [32], [33]
Image-based detection (edge/CNN)	Rapid presence/severity corroboration	Fast field checks; complements forecasts	Lighting/device shift; needs relabeling	Labeled images; basic QA	Human spot checks; confusion audits	[26], [31]
Microclimate fusion	Reduce station–canopy mismatch	Better local signal; improves thresholds	Sensor drift; placement bias	Canopy T/RH; leaf-wetness; bias vs station	Bias audits; uptime monitoring	[15], [51]
Ontology + expert rules	Explainable, auditable advisory	Clear reason codes; safe options	Rule sprawl; term drift	Curated entities/relations; thresholds	Rule regression tests; change logs	[34], [39]–[46]
IoT + learning pipeline	End-to-end sensing→advice→app	Delivery proven; QC integrated	Data gaps can break chains	QC'd sensor streams; app telemetry	Packet-loss tests; latency checks	[27], [62]

Across studies, a relatively small set of predictors appears repeatedly, with the main variation lying in how these predictors are transformed and validated.

Table 2. Predictors and transformations commonly used

Predictor / feature	Typical transform	Rationale	QA / notes	Refs
Temperature	Degree-days; short moving averages	Links to insect development and stage timing	Verify base temperature; station bias checks	[7], [21]
Rainfall	Weekly sum; 1–2 week lags	Moisture effects on pest dynamics and fungus	Fill gaps conservatively; flag outliers	[19], [22]
Relative humidity	Weekly mean; lag structure	Affects survival and spread	Co-check with canopy RH if available	[7], [22]
Wind	Weekly mean	Transport and drying effects	Smooth gusty days; ensure anemometer health	[19], [20]
Crop stage	Binary/ordinal flags	Aligns risk with phenology	Keep sowing/flowering logs accurate	[7], [23]
Microclimate bias	Station→canopy bias correction	Reduces site mismatch	Node placement and drift audits	[15], [51]
Image features	Edge/CNN embeddings	Presence/severity corroboration	Relabel per season; handle low light	[26], [31]
Soil moisture	Weekly median; thresholds	Irrigation stress interacts with pest risk	Sensor calibration; depth notes	[51]
Water quality (pH/EC)	Threshold flags	Guards fertigation/irrigation advisories	Calibrate probes; periodic lab cross-check	[62]
Composite lags	1–3 week lagged weather	Captures delayed effects	Test multiple lag specs; keep parsimonious	[19], [22], [23]
Yield proxies	Prior yield; NDVI windows	Link alerts to outcomes	Use cautiously; district effects matter	[32], [33]

4. KNOWLEDGE-BASED SYSTEMS AND ONTOLOGIES

Explainability is one of the strongest themes across the cotton DSS literature, and knowledge-based systems are central to that strength. Expert systems such as AMRAPALIKA showed early on that agronomic reasoning could be structured into transparent rule flows that field users could follow and revise [34]. Later systems for cotton and related crops extended this pattern by encoding symptoms, crop stages, actions, and advisory logic into rule engines and web/mobile front ends [24], [25], [35], [36], [47], [49], [50].

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Ontology-driven approaches deepen this by providing a formal vocabulary for crop, pest, stage, symptom, threshold, and action [39]–[46]. Their practical value lies in consistency. When sensors, dashboards, rules, and model outputs share the same conceptual layer, recommendations remain legible and updates become safer. In a real deployment, this means one threshold change can propagate across advisory text, app alerts, and backend logic without silent mismatch. This matters operationally because a shared ontology reduces inconsistency between sensor labels, advisory text, and backend rules, which in turn lowers update errors during the season.

The newer agent papers build directly on this idea. An intelligent farm expert MAS and related knowledge-based frameworks effectively extend expert-system logic into distributed roles, where agents can query, reason, and act using shared knowledge objects [57], [61]. This makes ontologies more than a documentation aid; they become the glue that keeps agent behavior aligned across modules.

5. SENSING AND MACHINE LEARNING

Sensing and machine learning contribute where direct observation or nonlinear interactions matter. Imaging work has shown that even lightweight edge features or CNN pipelines can rapidly confirm disease or pest presence, making them useful complements to weather-based forecasts [26], [31]. In cotton specifically, image-based techniques help answer a very practical question: whether a predicted high-risk week actually shows field evidence strong enough to justify intervention.

IoT-based sensing broadens this further. Low-cost station networks, microclimate nodes, moisture sensors, and telemetry pipelines make continuous monitoring more realistic than periodic manual logging. One important lesson from this stream is that good QC and robust delivery usually matter more than marginal gains in model complexity [27]. A model cannot support field decisions if the device clock is wrong, the moisture probe is drifting, or the data gap is silently filled with nonsense.

Machine learning brings value when it is applied selectively. LSTM, tree ensembles, and related approaches can capture interactions and longer lag structures that simple baselines miss [23], [27], [32], [33]. But they also bring maintenance burdens: drift, overfitting, and poor behavior under out-of-distribution weather. This is why the most credible papers pair ML with stronger validation designs and clearer operational context. The evidence base can be read most clearly when organized pest by pest, because lead time, validation design, and the role of sensing differ across targets.

Table 3. Pest-wise evidence snapshot (representative)

Pest/target	Representative models	Typical lead	Core predictors	Validation design	Representative sources
Whitefly	ZINB/hurdle; ML add-ons	1–2 weeks	Lagged T/RH/rain; stage flags	Site-wise CV; district holdouts	[19], [20], [22], [27]
Jassid	GLM/GLMM; ZINB; ML	1–2 weeks	Lagged weather; stage	Site-wise CV; label QA	[9], [11], [22], [23]
Thrips	GLM/GLMM; ZINB	1–2 weeks	Lagged weather; humidity	Site-wise CV; zero-rate checks	[9], [11], [23]
Pink bollworm	Degree-day rules	Stage windows	Degree-days; temperature	Year-wise splits; trap corroboration	[21]
Leaf diseases	Edge/CNN image detection	Near real time	Image features	Human spot checks; confusion matrix	[26], [31]
Yield links	Ensembles; regressors	Seasonal	Multi-var weather; stage	Site/district holdouts	[32], [33]

6. AGENT-BASED RESOURCE OPTIMIZATION AND DELIVERY

Although several of the newer agent and IoT studies are not cotton-specific, they provide directly transferable design patterns for cotton operations, especially in irrigation scheduling, mission planning, and advisory delivery. The newer literature adds an important control layer to cotton DSS: agents that coordinate actions, not just predictions. This is where the paper's scope broadens from pest intelligence to operational resource use.

Mixed-cropping irrigation agents are a clear example. Instead of applying a fixed rule to all plots, agent-based irrigation management ranks fields by utility, growth stage, soil, and drought sensitivity, then allocates scarce water accordingly [54]. This

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structure is appealing because it mirrors real agricultural trade-offs while making them explicit and repeatable. It also fits cotton systems where different plots may sit in different growth stages or face distinct moisture conditions.

Mission-planning papers extend the same logic to field operations. Precision farming tasks such as scouting or spraying can be framed as multi-objective problems involving time, energy, and operational risk [55]. Agent-based or auction-like allocation across UAVs or other assets then turns a forecast into an executable plan. This matters for cotton because even an accurate risk estimate has limited value if the sprayer, scouting team, or drone cannot act in the right window.

Fuzzy cognitive maps and agent hybrids contribute in another way: they preserve causal structure under uncertainty [56]. These systems are useful when field conditions are changing, data are incomplete, or farmer preferences need to be represented in the logic. Rather than hiding those uncertainties inside a black-box model, they expose relationships and trade-offs in a way users can discuss.

IoT delivery completes the loop. Monitoring systems and advisory agents bring together sensing, prediction, action logic, and app-level communication [59], [60], [62]. In many cases the main engineering challenge is not the model itself but keeping field nodes synchronized, handling intermittent connectivity, and exposing recommendations in a form that is short, credible, and actionable. The practical value of these systems depends not only on predictive accuracy but also on upkeep, failure handling, and the minimum data required to keep each design pattern honest in production. The operational implications of the reviewed design patterns are summarized in Table 4, with emphasis on maintenance burden and common failure modes.

Table 4. Design patterns for explainable, maintainable cotton DSS and agent systems

Pattern	When it makes sense	Minimum data to keep it honest	Ops upkeep	Common failure modes	Examples
Degree-day rules	Phenology-driven pests and stage timing	Daily Tmax/Tmin near fields; sowing dates	Recalibrate thresholds by region; update base temps yearly	Mis-timed windows if sowing dates are off; station bias	[7], [21]
Hurdle/ZINB counts	Sucking pests with zero-heavy trap counts	Weekly weather with 1–3 week lags; trap counts	Check station uptime; refit each season with zero-rate check	Inflated risk under station outages; over-dispersion drift	[19], [20], [22]
Time-series ML	Nonlinear responses; longer lags; multi-var risk	Multi-year weather; stage markers; enough labels	Monitor drift; keep a simple baseline for fallback	Silent decay; overfit to one district	[23], [27], [32], [33]
Image detection	Rapid leaf/trap confirmation and severity	Labeled images; basic QA; field lighting notes	Re-label samples; spot-check confusion cases	Domain shift across phones or lighting	[26], [31]
Microclimate fusion	Station–canopy mismatch; canopy effects	Canopy T/RH; bias correction vs station	Sensor maintenance; periodic bias checks	Sensor drift; gaps during rains	[15], [51]
Ontology + rules	Need for traceable reasons and audits	Curated entities/relations; threshold library	Rule curation; change logs; conflict tests	Rule sprawl; stale labels	[34], [39]–[46]
IoT + DL pipeline	End-to-end sensing → advice → app	QC'd sensor streams; app telemetry	Gap-fill; watchdogs; latency checks	Data gaps; over-trust in a single score	[27], [62]
Multi-agent irrigation	Mixed crops, limited water/energy, rotation	Plot map; soil moisture; pump schedules	Policy review pre-season; override paths	Oscillation when agents compete	[54]
Planning/mission agents	Route scouting, trap service, spray windows	Spatial graph; risk map; time windows	Re-solve with new constraints daily	Missed windows under rain; path churn	[55]
Fuzzy-agent hybrids	Uncertain rules, farmer preferences	FCM weights; agent roles; qualitative states	Re-weight under drift; sanity checks	Over-tuning; opaque side-effects	[56]
Advisory agent hubs	Weather, sensors, knowledge in one place	Forecast feed; soil sensors; disease models	Back-pressure; reason codes; A/B updates	Advice without reason; stale models	[59], [60], [62]

7. INTEGRATION BLUEPRINT

The combined literature supports a staged deployment path that begins with interpretable baselines and progressively adds corroboration, coordination, and delivery layers. A phased approach is important because it allows validation and operator trust to grow before more adaptive layers such as ML-assisted prioritization or agent-based coordination is introduced. Start with a transparent weather baseline using short lags and degree-days. Add microclimate and image checks only where they resolve meaningful uncertainty. Place an ontology-backed rule layer on top to encode thresholds, safe options, and explanation logic. Introduce ML when it clearly improves calibrated risk, not merely average accuracy. Use agents to coordinate scarce resources such as irrigation time, scouting capacity, and edge computing. Keep delivery robust with store-and-forward telemetry, edge fallbacks, and simple mobile or web interfaces.

This stack works because each layer has a clear job. Weather models detect risk. Ontology rules explain and constrain. Agents coordinate action. IoT keeps the loop alive. When something fails, the system can degrade toward simpler, safer behavior instead of collapsing into silence or nonsense.

8. PERSISTENT CHALLENGES AND NEAR-TERM OPPORTUNITIES

Several gaps remain. First, generalization across districts and seasons continues to reduce apparent performance; models that look excellent under random splits often weaken under realistic validation. Second, calibrated probabilities linked to economic thresholds remain underdeveloped in many papers. Third, the maintenance cost of sensors, rules, and models is still underreported, even though it determines real-world viability. In practice, imaging systems function best as corroborative layers rather than as stand-alone forecasting systems, especially under variable field lighting and device conditions.

For agent systems specifically, reward design and coordination policies need care. Irrigation or routing agents can optimize the wrong thing if fairness and operational constraints are not explicit. Connectivity and device health are also structural risks. This is why observability, versioning, and safe rollback matter as much as model quality. The strongest path forward is not one giant model, but a well-behaved stack with clear contracts between components. A related operational challenge is safe degradation under failure. Sensor drift, missing telemetry, out-of-distribution weather, and conflicting agent recommendations can all degrade decision quality. Systems intended for field use should therefore include uncertainty flags, fall-back rules, and rollback to the last stable model or threshold set.

9. CONCLUSION

Explainable agent systems offer a realistic next step for cotton farming. The strongest evidence still comes from modest, interpretable baselines: weather, stage, degree-days, and threshold logic. But those baselines become far more useful when wrapped in a delivery layer that senses reliably, coordinates assets, explains actions, and adapts without becoming opaque. The cotton DSS literature provides the biological and advisory backbone; the newer agent and IoT literature adds coordination and operational resilience. Together, these strands define a practical and scalable architecture for cotton farming in which prediction, explanation, coordination, and delivery remain aligned under real field constraints.

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