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Integrated Assessment of Cotton Yield: Parametric Identification and Production Forecasting for Pakistan

by

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CERTIFICATE OF APPROVAL

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(Rafia Haq Nawaz)

Abstract

Pakistan's cotton production has experienced a severe decline of over 50% over the past two decades, with the Bahawalpur division representing a critical epicenter of this agricultural crisis. Literature frequently evaluates agronomic and climatic factors in isolation or relies on opaque predictive algorithms, the exact directional drivers of this localized yield collapse have remained ambiguous. To address this gap, this study develops an integrated, diagnostic machine learning framework to evaluate regional yield constraints in Bahawalpur (2021–2025) and forecast national production trends for Pakistan (2026–2030). The methodology utilizes a three-part analytical approach: applying Random Forest permutation importance with negative correlation weighting to strictly isolate "decline-only" farm-level practices; constructing a Directional Climatic Stress Index (DCSI) to quantify abiotic stress during the highly sensitive July–September reproductive window; and benchmarking comparative time-series models (ARIMA, Linear Regression, Decision Tree, and Random Forest) for future macro-level projections. The diagnostic results reveal a systemic transition from biotic pest pressures to a "Dual-Water-Failure," identifying erratic macro-level monsoon precipitation and inadequate micro-level irrigation cycles as the absolute primary constraints on crop physiology. For future forecasting, the Random Forest ensemble demonstrated superior predictive stability (achieving 85.52% accuracy and a 14.48% Mean Absolute Percentage Error). Ultimately, this research concludes the better understanding for policymakers, extension workers, and farmers themselves, the hope is that this kind of diagnosis can point toward more targeted interventions.

Keywords: Cotton decline; Agronomic & climatic analyses; Cotton forecasting; Traditional & machine learning models; Climatic stress; Bahawalpur division

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Abbreviations

AIC	Akaike Information Criterion
APSIM	Agricultural Production Systems Simulator
ARIMA	Autoregressive Integrated Moving Average
CCPs	Conventional cotton producers
CNNs	Convolutional Neural Networks
CSA	Convolutional Self-Attention
CSI	Climatic Stress Index
DCSI	Directional Climatic Stress Index
DL	Deep Learning
DNNs	Deep Neural Networks
DT	Decision Trees
EBM	Explainable Boosting Machine
EO	Earth Observation
FedGAvg	Federated Gaussian Average
GDD	Growing Degree Days
GEI	Genotype-environment interaction
IoT	Internet of Things
LRP	Layerwise Relevance Propagation
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MET	Multi-environment trials
ML	Machine Learning

NDVI	Normalized Difference Vegetation Index
Ofertname	Other fertilizer Name
RF	Random Forest
RMSE	Root Mean Squared Error
RNNs	Recurrent Neural Networks
SAR	Synthetic aperture radar
SBC	Schwarz Bayesian Criterion
SCPs	Sustainable cotton producers
SHAP	Shapley Additive explanations
WGP	Water-Genetics-Precision
XAI	Explainable artificial intelligence
XGBoost	Extreme Gradient Boosting

Chapter 1

Introduction

1.1 Background

Cotton occupies a central place in Pakistan's economy and rural life. Often called "white gold," it has historically been one of the country's most valuable cash crops, contributing significantly to foreign exchange earnings and supporting millions of livelihoods across the agricultural supply chain. The textile industry, which relied almost entirely on domestically produced cotton, forms the bedrock of Pakistan's manufacturing sector, employing a substantial portion of the industrial workforce and accounting for a major share of national exports. A decline in cotton crops has affected significantly farming communities and exporters, who find it difficult to fulfill their needs. However, this critical agricultural pillar faces severe threats from environmental instability. The annual temperature profile for cotton growing regions in Pakistan, the crop is subjected to extreme thermal fluctuations where temperatures often reach as high as 50°C. These harsh conditions create significant heat stress, which, when combined with other abiotic and biotic pressures, complicates efforts to maintain production levels [1].

The numbers, when viewed over the past two decades, reveal a deeply concerning trajectory. Pakistan's cotton production peaked at approximately 14 million bales in the 2004–05 season, a high point that seemed to promise continued growth and prosperity for the sector. Since then, however, the trend has been decreasing. Production has slid to barely 5 to 6 million bales in 2017–20, representing a decline of more than 50% from that peak. These are not minor fluctuations from year to year, but a sustained erosion of productive capacity that demands serious investigation [2]. The data reveals a concerning trend in Pakistan's cotton sector characterized by a simultaneous decline in both cultivated area and total production volume. Cotton yield per hectare has remained largely stagnant, the overall reduction in harvested land and volatile production levels highlights the increasing vulnerability of the sector to ongoing agricultural challenges [3].

Punjab province, which contributes nearly 70% percent of national cotton output, has been at the epicenter of this decline. The 2024 season alone saw a staggering 36.49% reduction in production compared to previous years, a collapse that cannot be explained by routine seasonal variation. Within Punjab, certain districts have been hit harder than others. Bahawalpur division, located in the southern part of the province, has historically been one of the most reliable cotton producing areas. Its soils and climate were once considered ideally suited to cotton cultivation, and generations of farmers relied their livelihoods around the crop. Today, that reputation is under threat. Fields that once produced reliable harvests and farmers who have grown cotton their entire lives are questioning whether it remains a viable crop for them [4].

The reasons for this decline are not straightforward. Conversations with farmers, consultants, and agricultural officials point to a complex mix of factors. Pesticides, particularly from bollworm and whitefly, have intensified in recent years, sometimes reaching outbreak levels that devastate entire fields [5]. Input costs for fertilizer, pesticides, and irrigation have risen steadily, squeezing profit margins. Specifically, the cost of plant protection has experienced the highest growth rate among all inputs at 8.98%, driven by an increasing intensity of pest attacks that necessitate more frequent chemical applications. This upward trend in production costs, combined with lower sale prices for cotton, has frequently forced farmers into negative net returns, as seen during the 2002, 2006, and 2007 production years.

Consequently, many growers, faced with these shrinking margins, are increasingly considering a shift toward more economically viable competitive crops, such as rice or sugarcane [6]. Seed varieties that once performed reliably have shown inconsistent results. Weather patterns have become less predictable, with extreme temperatures and erratic rainfall disrupting traditional planting and harvesting schedules [7]. And beneath all of these lies a deeper question: are these problems temporary setbacks or symptoms of more fundamental shifts in the agricultural and climatic systems that have supported cotton production for decades?

What makes Bahawalpur a particularly important case study is that it sits at the intersection of multiple stressors. As a semi-arid region, it has always been vulnerable to water scarcity, but rising temperatures and changing rainfall patterns have amplified this vulnerability. The division also represents a typical cross section of Punjab's cotton farming community, with a mix of large landholders and smallholders, farmers who rely on traditional practices alongside those who have adopted newer technologies. Understanding what is happening in Bahawalpur can therefore shed light on the broader challenges faced in the cotton production across the province and the country [8].

Despite the urgency of the situation, most existing studies have approached the problem in fragments. Some have examined pest dynamics in isolation, others have focused on climate trends, and still others have analyzed economic factors such as input prices or market access. What has been missing is an integrated analysis that brings these pieces together, which must address not just which factors correlate with yield, but which ones are actively contributing to the observed decline. Moreover, while machine learning models have been increasingly applied to crop yield prediction in recent years, they have often operated as black boxes, providing accurate forecasts but little insight into the underlying drivers. They use older datasets that do not reflect current ground realities. And when machine learning is applied, it focuses on prediction rather than identifying which specific parameters are actively pulling yields down [9]. Studies have demonstrated the power of algorithms like Random Forest, highlighting their potential for agricultural applications while also underscoring the need for explainability if these tools are useful in making the informed and practical decisions [10].

This study is an attempt to fill this gap by focusing and developing methods designed to isolate factors that are pulling yields down rather than simply identifying correlations. It also aims to provide a diagnosis that is both rigorous and actionable. The three-part analytical framework parametric identification for agronomic factors, a directional climatic stress index for weather variables, and comparative forecasting for future production offers a template for integrated assessment facing similar challenges. The stakes are high. Cotton is not just another crop in Pakistan; it is combined with the country's economic structure, its rural social fabric, and its position in global textile markets. If the decline in Bahawalpur and similar regions continues unchecked, the consequences will extend far beyond the farm gate. This study proceeds from the conviction that understanding the problem is the first step toward solving it.

1.2 Problem Statement

Cotton production in Pakistan has fallen by more than half over the past two decades, from 14 million bales in 2004-05 to barely 5 to 6 million bales today [11]. Punjab, which accounts for nearly 70% of national output, saw a 36.49% reduction in 2024 alone [12]. Bahawalpur division, once a reliable cotton hub, is now witnessing farmers abandon the crop. The problem is that no one can say with certainty which factors are actually causing the decline. Most existing studies examine agronomic and climatic factors in isolation or rely on elementary statistical models [13].

Despite the severity of this systemic collapse, there remains a critical ambiguity regarding the precise, directional factors actively driving the decline. Most existing research approaches the crisis in fragments, examining agronomic constraints, pest dynamics, and climatic stressors in strict isolation, or relying heavily on elementary statistical models that fail to capture complex environmental interactions. Ultimately, the central problem is the profound absence of an integrated, decline-focused diagnostic framework capable of evaluating localized agronomic and climatic data simultaneously to definitively isolate which specific parameters are actively harming yields in vulnerable regions like Bahawalpur.

1.3 Research Questions

This study is structured around by the following research questions:

i. Which Machine Learning isolates and ranks agronomic factors are actively contributing to cotton yield decline?

ii. Which critical climatic stressors suppress yield during the sensitive reproductive months, and how can their directional impact be mathematically quantified?

iii. What are the projected national cotton production trends for Pakistan (2026 – 2030), and which comparative forecasting model provides the highest predictive reliability?

1.4 Research Objectives

The primary objectives of this study are as follows:

i. To identify and rank the agronomic factors contributing to regional yield decline by combining Random Forest permutation importance with negative correlation weighting.

ii. To determine critical climatic stressors during the July–September window and construct a Directional Climatic Stress Index (DCSI) to quantify their impact on yield.

iii. To forecast national cotton production trends for the next five years and evaluate the comparative reliability of advanced time-series predictive models.

1.5 Significance of the Study

This study holds significance on multiple levels: practical, methodological, and policy relevant. For farmers across Punjab, the study offers a systematic diagnosis of the most relevant and responsible factors for yield decline. By identifying specific agronomic practices, input choices, and pest pressures that are actively pulling yields down, it provides a basis for more informed decision making at the farm level. A farmer who knows, for example, that certain pesticide regimes or seed varieties are consistently associated with lower yields can adjust practices accordingly. The study does not prescribe solutions, but it does highlight where attention is most urgently needed. For extension workers and agricultural advisory services, the study offers a template for translating complex analytical results into actionable guidance. The combination of Random Forest importance with correlation-based directionality provides a transparent way to rank factors not just by how much they matter, but by whether they matter in a positive or negative direction. This kind of clarity is essential for designing effective extension messages and targeting support programs. For policymakers, the study provides evidence-based input for decisions about research priorities, subsidy programs, and climate adaptation strategies. If the analysis points to specific pest pressures as dominant drivers of decline, resources can be directed toward integrated pest management research and extension. If climatic stress, particularly from temperature or humidity during critical growth stages, emerges as a key factor, that argues for investment in climate resilient varieties and irrigation infrastructure. The forecasting component adds a forward-looking dimension, helping planners anticipate future production levels and prepare accordingly.

Methodologically, the study contributes to the growing literature on interpretable machine learning in agriculture. The parametric identification approach offers a way to open the black box of Random Forest models and extract not just variable importance rankings but directional insights that are directly relevant to intervention design. The Directional Climatic Stress Index provides a flexible framework for incorporating biological knowledge about stress directions into climate impact assessment, moving beyond simple correlation or variance analysis. For researchers working on cotton in Pakistan and similar environments, the study offers a baseline against which future work can be compared. The identification of critical factors in the 2021 to 2025 period can serve as a reference point for tracking how these relationships evolve over time as climate changes, pest pressures shift, and new technologies emerge.

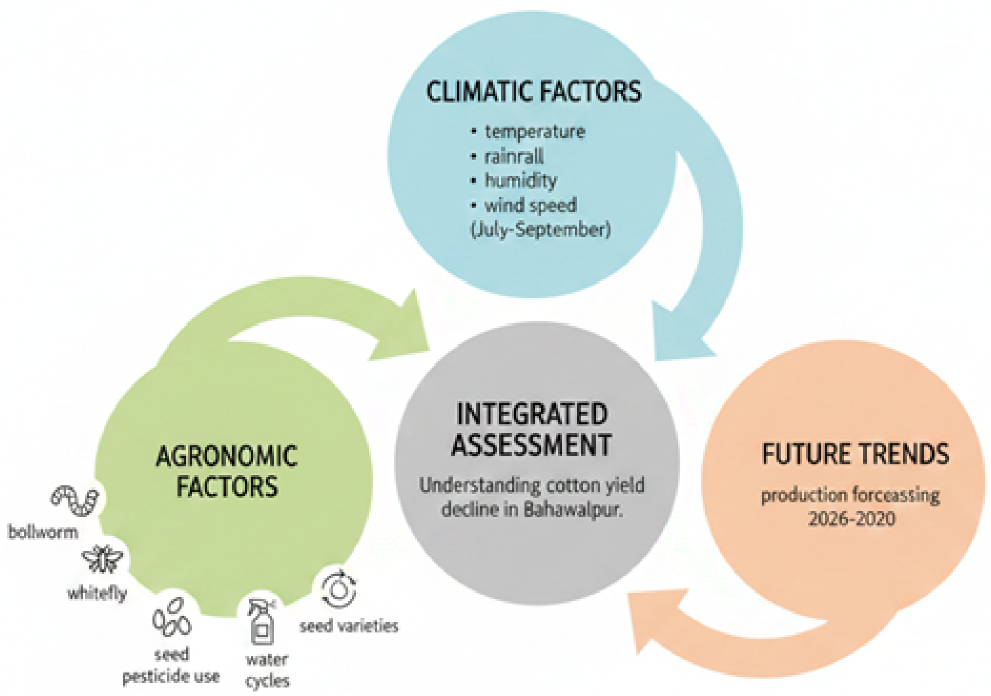


FIGURE 1.1: Cotton yield assessment model (Source: Original to this study)

Finally, the study contributes to the broader effort to understand and reverse the decline of cotton production in Pakistan. By focusing on Bahawalpur, this study aims to generate insights that are both locally relevant and more broadly applicable. This kind of integrated, decline focused analysis can help in shifting the conversation from describing the problem to identifying actionable entry points for addressing these problems.

1.6 Thesis Structure

This thesis is organized into following chapters, each addressing a distinct component of the research.

Chapter 2 presents a review of literature relevant to this study. It covers three main areas: machine learning applications in crop yield prediction with emphasis on the important methods; studies on climate impacts on cotton production, particularly those identifying critical growth stages and stress factors, and existing research on cotton yield in Pakistan and similar environments. The chapter identifies gaps in the literature and positions this study within the broader research landscape.

Chapter 3 describes the research methodology in detail. It is organized into three sections corresponding to the three analytical components of the study.

i. The first section covers the parametric identification approach, including data sources from the Punjab Crop Reporting Service, data cleaning and preprocessing steps, the Random Forest model specification, permutation importance calculation, and the negative correlation weighting procedure.

ii. The second section describes the Directional Climatic Stress Index, including data sources from Bahawalpur Division meteorological records, the selection of critical months, Z-score calculation, stress direction definitions, and the weighting procedure linking weather anomalies to the observed yield drops.

iii. The third section covers the forecasting analysis, including the Karachi Cotton Association data, feature engineering for time series forecasting, model specifications for ARIMA, Linear Regression, Decision Tree, and Random Forest, and the evaluation metrics used to compare model performance.

Chapter 4 presents the results and discussions of the analysis. It follows the same three-parts structure as the methodology, presenting findings from the agronomic decline identification, the climatic stress index, and the forecasting models. Tables and figures are used to illustrate key results, including ranked lists of decline contributing factors, stress index values for different climatic parameters, and forecasted production levels alongside model performance metrics.

Chapter 5 concludes the thesis with a summary of the main findings, limitations and strength of the study and suggestions for future research. It returns to the broader question of what can be done to address cotton decline in Bahawalpur division and similar regions, offering reflections on the path forward.

Chapter 2

Literature Review

The literature review serves as the foundational source for understanding the multifaceted crisis of cotton yield decline in Pakistan. The existing research is systematically synthesized across three primary domains; the contextual and historical realities of cotton farming, the agronomic and climatic stressors driving production losses, and the computational methodologies used for yield prediction. By critically examining the intersection of traditional agricultural studies and advanced predictive analytics, this chapter scopes the boundaries of current knowledge regarding crop forecasting and environmental interactions. Ultimately, the primary purpose is to identify critical methodological and conceptual gaps in the literature that justify the need for an integrated, diagnostic approach to yield decline rather than relying purely on conventional predictive modeling.

2.1 Contextualizing the Cotton Crisis in Pakistan

2.1.1 Economic Impact and Historical Production Trends

Cotton operates as the central, indispensable pillar of Pakistan's agricultural and industrial economy, traditionally earning the moniker of "white gold" due to its immense contribution to the national GDP and foreign exchange revenues. The domestic textile industry, which absorbs the vast majority of the local cotton harvest, represents the largest manufacturing sector in the country and is responsible for employing millions of individuals across both rural and urban landscapes. Beyond the direct production of lint for the textile sector, the cotton crop is intricately tied to the broader agricultural ecosystem, providing critical by-products such as cottonseed oil that fulfill a substantial portion of Pakistan's domestic edible oil requirements. Furthermore, the protein-rich cottonseed cake remains a primary, cost-effective feed source for the national livestock industry, meaning a deficit in cotton production triggers inflationary pressures across multiple food security domains. As domestic yields have continued to stagnate, the formidable textile sector has been forced to increasingly rely on imported raw cotton to sustain factory operations and fulfill international export orders. This heavy reliance on agricultural imports has severely exacerbated Pakistan's trade deficit, draining precious foreign exchange reserves and diminishing the overall global competitiveness of the nation's textile exports. Meteorological analyses demonstrate that daily maximum temperatures in these major cotton-producing belts frequently surge between 45°C and 50°C, pushing the biological limits of even the most heat-adapted cotton cultivars. Consequently, the historical downward trajectory in crop performance transcends localized agronomic failure, representing a macroeconomic vulnerability that destabilizes both rural livelihoods and the broader industrial trade balance [1].

The historical production trends also reflect a troubling structural shift in domestic land-use patterns, driven primarily by the increasing economic isolation of local growers. On facing compounding environmental stressors, escalating input costs, and diminishing profit margins, a significant proportion of traditional cotton farmers have systematically diverted their acreage toward more resilient and financially lucrative cash crops, such as sugarcane and maize. This crop substitution is particularly evident across the historical cotton belts of Punjab, where inadequate policy support and volatile market pricing have accelerated the transition away from the cultivation of white gold. While this agricultural displacement provides essential short-term financial relief for individual farming households, it critically undermines the long-term supply chain architecture of the national textile industry. Therefore, reversing this prolonged two-decade decline requires a holistic approach that not only addresses the agronomic determinants of yield loss but also restores the foundational economic viability of cotton cultivation for the producer [2].

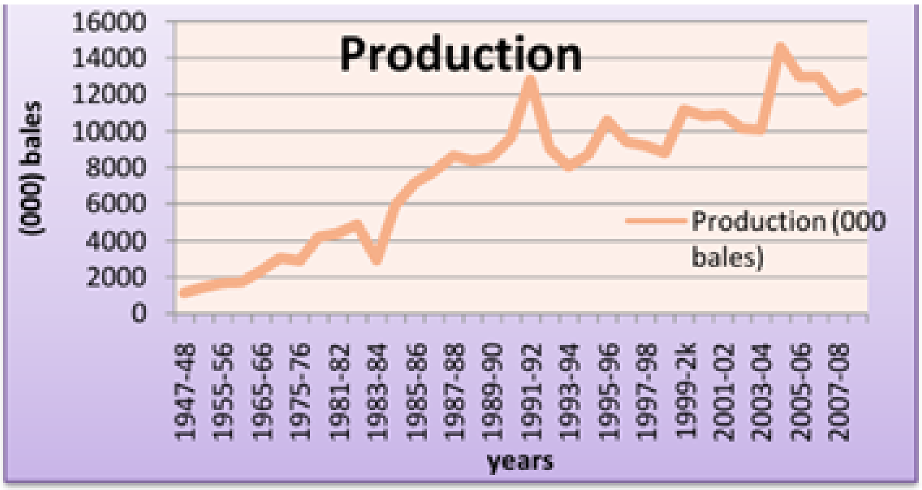
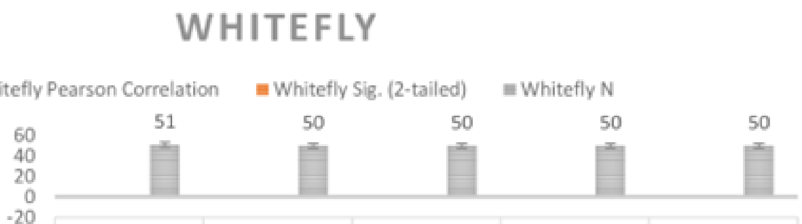


Figure 2.1: Historical trends of cotton production (in '000' bales) in Pakistan from 1947–48 to 2007–08 [6]

Historically, the early 2000s marked a golden era for Pakistani cotton, with national production peaking at an impressive 14 million bales during the 2004-2005 growing season. However, this promising trajectory has suffered a severe and sustained reversal over the past two decades, with production volumes collapsing to a precarious 5 to 6 million bales by the 2023-2024 season [3]. This alarming reduction of over 50% represents a systemic erosion of the nation's agricultural capacity, directly threatening the operational viability of the entire textile supply chain and the socioeconomic stability of farming communities.

2.1.2 Bahawalpur Division: A Microcosm of Yield Decline

As the major agricultural crisis affecting Southern Punjab, the Bahawalpur division serves as a critical and highly representative microcosm for investigating the multi-layered drivers of cotton yield degradation. Historically celebrated as one of the most reliable and fertile hubs for cotton cultivation, Bahawalpur possesses the ideal soil composition that previously guaranteed robust harvests and sustained the livelihoods of generations of local farmers. In regions like the Bahawalpur Division, where the agricultural economy faces severe threats from pests and foliar diseases, the ability to rapidly diagnose crop health is paramount for stabilizing yields [4]. The region is increasingly overwhelmed by compounding stressors, including severe, recurring outbreaks of whitefly and bollworm, which have been statistically linked to localized fluctuations in humidity and unseasonal rainfall events. Because Bahawalpur encapsulates a diverse cross-section of both large-scale and smallholder farming operations navigating these simultaneous climatic and agronomic crises, it provides an unparalleled localized environment for executing a highly targeted, diagnostic analysis of yield decline [5].



	Whitefly	Temperature	Humidity	Rainfall	Clear/cloud
Whitefly Pearson Correlation	1	0.076	-0.051	0	0
Whitefly Sig. (2-tailed)		0.599	0.726	0.009	0
Whitefly N	51	50	50	50	50

FIGURE 2.2: Correlation analysis of whitefly population dynamics with temperature, humidity, rainfall, and sky conditions in cotton crops [5]

The transition from traditional farming practices to chemically intensive management has inadvertently impaired the ecological fragility of the Bahawalpur division. Encountering with climate-induced pest infestations, local farmers have increasingly resorted to the uncalibrated, excessive application of synthetic pesticides and fertilizers in desperate attempts to salvage their diminishing harvests. Unfortunately, this reactive agronomic strategy frequently yields negative marginal returns, fundamentally degrading the natural soil health and increasing the economic burden on already vulnerable smallholder operations. These localized input inefficiencies compound the inherent environmental stressors, creating a destructive feedback loop where the soil's reduced water-holding capacity magnifies the biological impact of extreme thermal shocks. Consequently, understanding the yield crisis in Bahawalpur requires moving beyond broad meteorological observations to dissect how these specific, localized farm-level management practices interact with abiotic extremes [6].

2.2 Agronomic and Climatic Determinants of Cotton Yield

2.2.1 Critical Phenological Stages and Environmental Sensitivity

Cotton development proceeds through highly distinct phenological stages ranging from germination and vegetative growth to flowering and boll opening, each possessing strict environmental requirements. Cotton's sensitivity to climatic fluctuations is highly stage-specific, with the reproductive phase acting as the primary bottleneck for productivity. Research indicates that while cotton is resilient, temperatures exceeding 32°C during the critical flowering and boll-development stages significantly induce reproductive failure, characterized by reduced boll retention and increased abscission. This sensitivity is further compounded by the asynchronous development of reproductive organs under thermal stress, which disrupts pollination and ultimately limits the plant's capacity for carbohydrate accumulation. These findings underscore that the physiological window of flowering is not merely a growth stage but a high-risk period where environmental volatility translates directly into irreversible yield loss. While the deep taproot system of the cotton plant provides a baseline level of drought tolerance during early vegetative growth, the reproductive phases are exceptionally vulnerable to external shocks. Specifically, the transitional window from July to September, which encompasses the peak flowering and boll formation stages, dictates the ultimate trajectory of the harvest. Any deviation from optimal climatic norms during this highly sensitive period directly triggers physiological stress responses, frequently culminating in the irreversible shedding of fruiting bodies. Consequently, understanding the intersection between the plant's biological timeline and seasonal weather anomalies is paramount for diagnosing the root causes of systemic yield degradation [7].

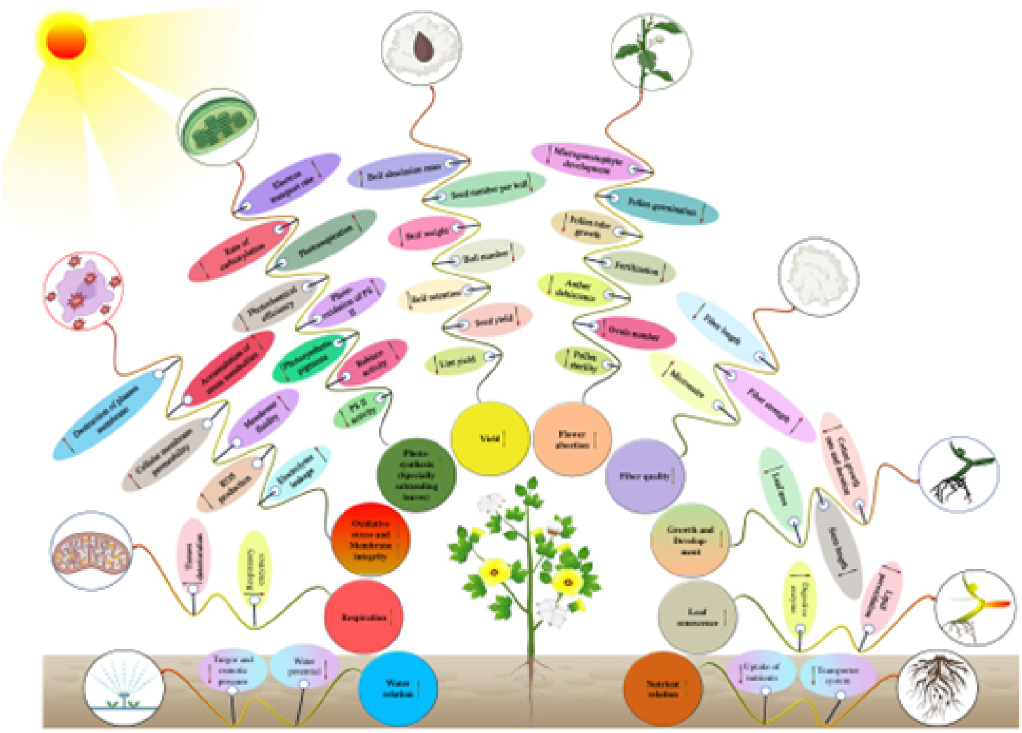


FIGURE 2.3: Impact of high day and night temperature regimes on cotton key traits; upward and downward arrows indicate the directional changes in specific metabolic, physiological, and yield-related parameters [7]

Expanding upon the critical July-to-September window, it is imperative to recognize that the intersection of peak monsoon humidity and maximum thermal radiation during these months creates a highly volatile microclimate. Furthermore, the adoption of sustainable cultivation practices plays a pivotal role in mitigating these phenological vulnerabilities. Evidence from the Bahawalpur and Rajanpur district demonstrates that sustainable cotton producers (SCPs) achieve higher resilience through the targeted use of stress-tolerant varieties and efficient input management compared to conventional cotton producers (CCPs). By aligning management practices such as optimized irrigation and strategic planting with the crop's biological timeline, these farmers can effectively buffer the plant against the climate-induced physiological shocks that typically degrade conventional yields. This socio-economic and agronomic evidence confirms that adaptive management is essential for safeguarding cotton production against the accelerating environmental pressures currently observed in Pakistan's core cotton regions [8].

2.2.2 Impact of Abiotic Stressors and Thermal Extremes

The structural integrity of the cotton crop is frequently compromised by complex, non-linear environmental stressors, where traditional black-box machine learning models often struggle to provide mechanistic clarity regarding yield decline. While advanced computational algorithms can achieve high predictive accuracy, they often neglect the directional interactions between variables like temperature and precipitation, which are essential for understanding how climate change impacts crop physiology. Beyond raw temperature thresholds, the integration of explainable artificial intelligence (XAI) has provided new insights into the non-linear and asymmetric nature of crop responses to climate stressors. Advanced statistical modeling indicates that crop yield does not respond linearly to climatic variables; instead, responses are often characterized by threshold-based interactions where the detrimental effects of thermal extremes are amplified by concurrent moisture deficits. For instance, machine learning analyses demonstrate that the impact of high temperatures is conditional on moisture availability, revealing that water demand typically increases non-linearly with warming to compensate for heightened evapotranspiration. By utilizing interpretable frameworks such as partial dependence plots researchers can now distinguish between the primary stressors, such as humidity or thermal shocks, and secondary variables, providing a more robust basis for developing climate-resilient agricultural strategies [9, 26]. Furthermore, recent diagnostic advancements have demonstrated that agricultural yield loss is not solely driven by isolated thermal shocks, but by compounding abiotic synergies that are highly context-dependent. By utilizing interpretable toolkits, such as partial dependence plots and variable interaction analysis, researchers can now isolate specific thresholds where environmental factors like maximum daily temperatures actively suppress productivity. This capability is critical for moving beyond generalized annual averages toward a precise, mechanistic understanding of how regional climatic volatility, when combined with site-specific management, drives the systemic degradation of crop health [10].

2.2.3 Regional Climatic Risks and Hydrological Challenges in the Indus Basin

The drastic decline in national cotton production is deeply tangled with the escalating climate vulnerabilities characteristic of the Indus Basin, particularly within the southern regions of Punjab province. Geographically situated in a highly arid to semi-arid climatic zone, Southern Punjab consistently experiences extreme environmental volatility, making its agricultural output highly susceptible to exogenous weather shocks and temperature anomalies The compounding nature of these abiotic stressors extends beyond immediate plant physiological failure to fundamentally degrade the underlying soil architecture of the Indus Basin. Prolonged exposure to extreme solar radiation coupled with high evaporation rates drastically depletes soil moisture reserves, leading to an increased concentration of surface salts and the gradual salinization of historically fertile agricultural land. This degraded soil profile significantly hinders the cotton plant's ability to efficiently uptake essential nutrients, magnifying the detrimental effects of thermal shocks during the peak reproductive months of July and August. Sophisticated diagnostic evaluations of these interacting variables confirm that managing isolated temperature spikes is largely ineffective if the underlying, localized soil moisture deficit is not simultaneously rectified. Therefore, effectively mitigating the climate vulnerability of Southern Punjab requires a comprehensive understanding of how these multidimensional abiotic factors directionally harm both the crop and its sustaining agronomic environment [11]. The accelerating impact of climate warming, characterized by rising temperatures and extreme heat events, has significantly disrupted cotton phenological development in regions like Punjab, Pakistan. Research indicates that sustained exposure to temperatures exceeding optimal ranges during critical stages such as flowering and boll development leads to irreversible physiological damage, including reduced boll retention, compromised fiber quality, and overall yield decline. Furthermore, as ambient temperatures increase, the duration of developmental phases from sowing to maturity is significantly compressed, limiting the crop's capacity for carbohydrate accumulation and reducing the potential for stable harvest outcomes [13].

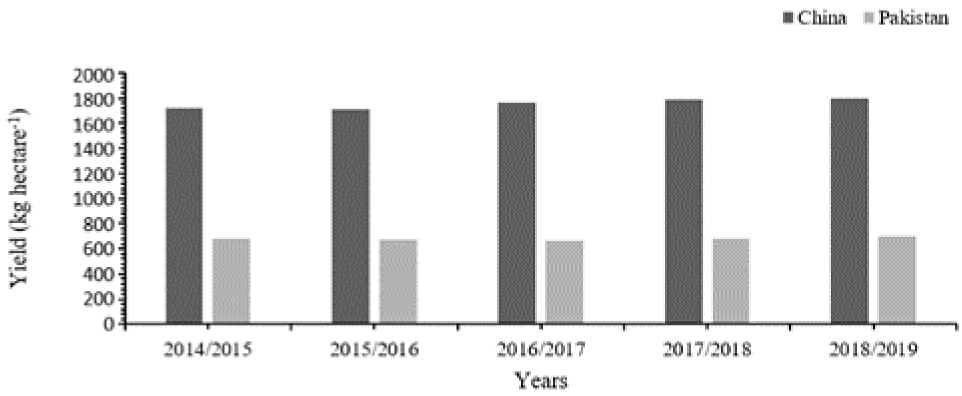


Figure 2.4: Yearly assessment of Pakistan and China, production [13]

Given the scarcity of continuous, reliable historical phenological datasets, agro-climatic indices offer a robust and innovative methodology for assessing cotton development stages. Indices such as Growing Degree Days (GDD) serve as a fundamental tool for correlating accumulated thermal units with specific biological phases, such as planting, square initiation, and boll opening. By establishing cardinal temperature thresholds which define the lower and upper bounds for successful growth these indices allow for the estimation of phenological timing even in the absence of systematic manual observations, providing a vital analytical framework for crop management under fluctuating environmental conditions [13, 14]. The agricultural viability of Southern Punjab is fundamentally dependent on the intricate network of the Indus Basin Irrigation System, which is becoming increasingly strained under the escalating pressures of climate change. As rising global temperatures alter historical weather patterns, the region experiences severe hydrological volatility, frequently characterized by unpredictable flash floods that abruptly transition into prolonged periods of acute water scarcity. This unpredictability directly threatens the delicate water balance required during the critical vegetative and flowering stages of the cotton plant, often resulting in severe drought stress that permanently stunts canopy development and induces early boll shedding. Conversely, when these semi-arid environments experience sudden, unseasonal monsoon downpours, the resulting waterlogging severely suffocates the deep taproot system while simultaneously creating a highly humid microclimate ideal for aggressive biological pests. Consequently, the reliance on traditional, inflexible irrigation scheduling is no longer sufficient, highlighting a critical need to understand how erratic hydrological cycles directly suppress yields in such vulnerable geographies [15].

2.2.4 Pest Dynamics and Input Management Inefficiencies

The biological health of cotton fields is inseparably linked to the surrounding climate, as shifting weather patterns directly orchestrate the proliferation of devastating agricultural pests. The escalating severity of these pest infestations is further complicated by the rapid evolutionary adaptation of insects to standard chemical control measures. Addressing these management inefficiencies requires transitioning from conventional, descriptive analysis to predictive frameworks that explicitly account for dynamic temporal dependencies. Recent advancements in Explainable AI (XAI) and hybrid deep learning models such as the integration of Long Short-Term Memory (LSTM) networks with SHAP provide the transparency necessary to isolate which management decisions or environmental anomalies are actively suppressing productivity. These models allow stakeholders to quantify the specific directional impact of individual factors, such as fertilizer dosage or pest control timing, thereby replacing intuitive, guess-based management with data-driven, actionable insights that align with long-term agricultural sustainability goals [16].

Beyond the immediate biological destruction caused by pest resurgence, these maladaptive management practices inflict severe, long-term degradation upon the

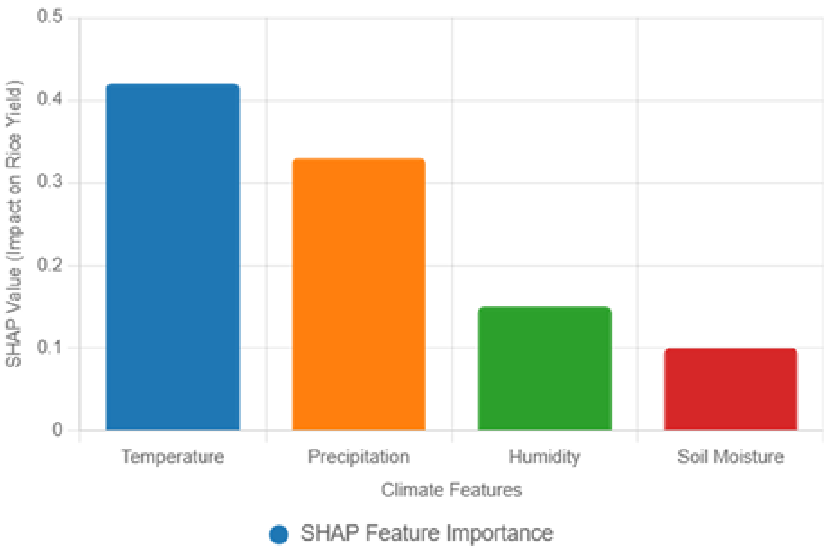


FIGURE 2.5: Feature importance ranking derived from the hybrid LSTM-SHAP model, showing temperature and precipitation as the primary drivers of rice yield variability [16]

region's foundational soil architecture. The continuous overloading of synthetic nitrogenous fertilizers, often applied to mistakenly compensate for stunted vegetative growth, rapidly alters the localized soil microbiome and aggressively increases soil salinity. This chemical saturation physically degrades the soil structure, drastically reducing its water-holding capacity and unintentionally exacerbating the underlying drought stress during peak summer thermal shocks. From a socioeconomic perspective, this relentless expenditure on ineffective agrochemicals aggressively shrinks the farmer's profit margin, transforming cotton cultivation into a highly precarious financial liability. Ultimately, restoring regional crop yields requires a fundamental departure from these panicked, chemically intensive applications in favor of climate-resilient agronomic interventions that prioritize long-term soil health [17].

2.2.5 Quantifying Weather Impacts: Indices and Modeling

To rigorously evaluate the magnitude of these intersecting stressors, researchers have increasingly turned toward mathematical indices and complex simulation frameworks capable of quantifying weather impacts. Traditional approaches have heavily utilized multiple linear regression and fixed-effect models to assign specific coefficients to isolated parameters, successfully mapping how variables like evaporation and sunshine duration mathematically drive down the number of retained bolls [18].

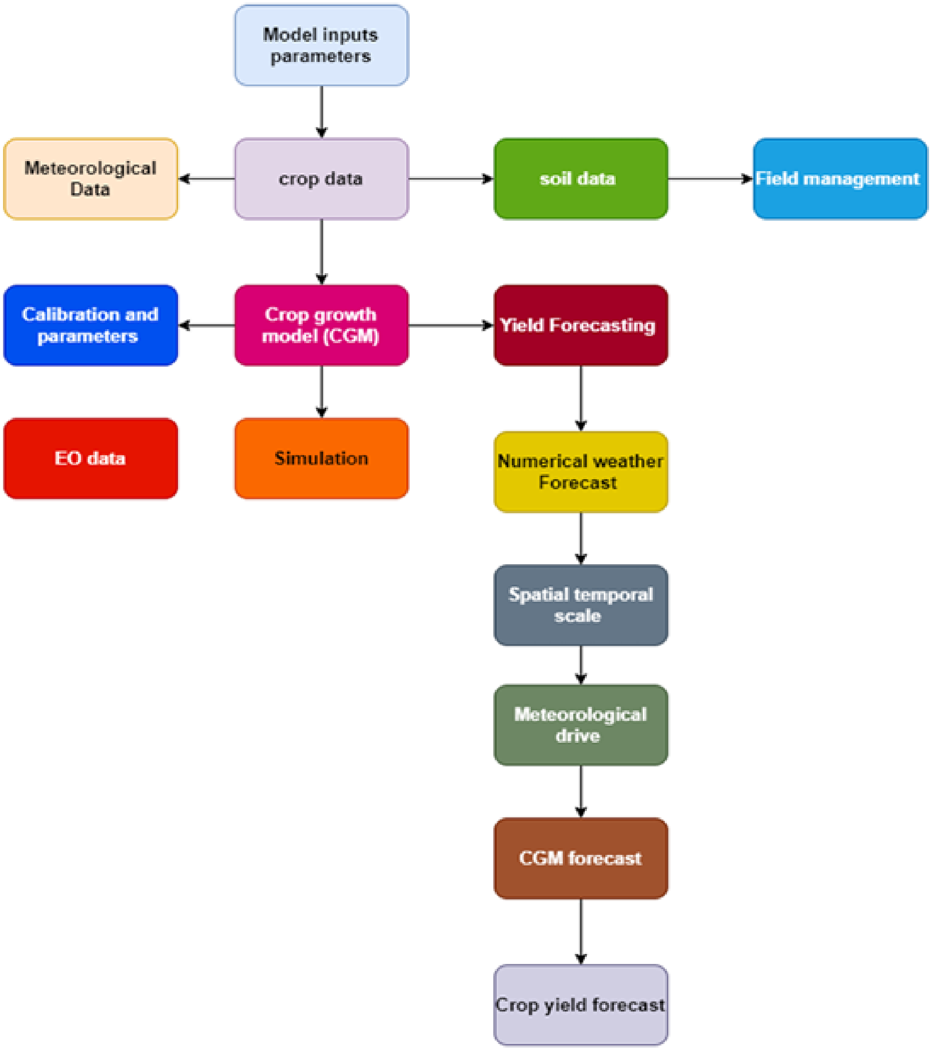


FIGURE 2.6: Methodological framework illustrating the integration of meteorological, soil, and crop data for crop growth modeling and yield forecasting [20]

In more advanced, temporally sensitive applications, studies have aggregated daily climate records into specific multi-day intervals (e.g., 5-day windows) to perfectly align meteorological data with the biological fruiting cycles of the cotton plant, thereby dramatically increasing predictive accuracy. The development of specialized agro-climatic indices has historically focused on broad temperature averages, often obscuring the acute, localized thermal shocks that actively devastate crop canopies. To accurately capture the true physiological burden placed upon the cotton plant, researchers must pivot toward indices that explicitly measure biological heat stress such as calculating accumulated thermal units strictly above the crop's cardinal failure threshold. By mathematically filtering out the baseline temperatures that support healthy vegetative growth, these refined calculations can successfully isolate the specific "decline-only" climatic variables responsible for reproductive failure. This highly targeted approach enables the construction of a Directional Climatic Stress Index, which specifically quantifies the cumulative magnitude of environmental harm inflicted during the most sensitive phenological windows. Implementing such specialized indices are absolutely essential for regions like Southern Punjab, where generalized weather models frequently fail to correlate broader warming trends with localized, catastrophic yield collapses [19].

Additionally, sophisticated crop simulation models such as the APSIM framework, have been deployed to simulate the physiological outcomes of shifting planting dates and varying crop densities under projected climate-warming scenarios. However, while these indices and models provide exceptional theoretical insights into general climate vulnerability, there remains a critical need to translate these simulations into localized, directional indices that can isolate the exact parameters harming real-world yields in targeted regions like Bahawalpur [20]. Beyond formulating isolated climatic indices, modern simulation frameworks are increasingly designed to process continuous environmental datasets to capture the dynamic progression of weather impacts over time. Rather than relying exclusively on static chronological markers, these advanced modeling architectures integrate lag-features that mathematically track how a severe weather anomaly in early July systematically degrades the harvest in late September. This temporal integration is critical because the biological damage inflicted by erratic monsoons or intense thermal radiation rarely manifests instantly, but instead creates a cascading physiological failure across subsequent developmental stages. By synchronizing these localized weather indices with real-time agronomic data, researchers can continuously monitor the cumulative stress load accumulating within the cotton canopy throughout the entire growing season. Ultimately, moving from static statistical summaries to dynamic, lag-integrated impact modeling provides the exact computational foundation required to transition from merely observing yield degradation to actively diagnosing its localized trajectory [21].

2.3 Predictive Analytics and Machine Learning in Agriculture

2.3.1 Evolution of Crop Yield Modeling and Algorithmic Approaches

For decades, agricultural yield forecasting relied heavily on traditional statistical techniques, primarily multiple linear regression and basic autoregressive models, to establish baseline relationships between environmental inputs and crop outputs. While these foundational models offered a high degree of mathematical simplicity, they frequently struggled to capture the complex, non-linear interactions inherent in dynamic agro-ecological systems. As the volume and dimensionality of agricultural data expanded incorporating continuous weather sensor feeds, high-resolution satellite imagery, and granular soil metrics; the field experienced a paradigm shift toward advanced Machine Learning (ML) and Deep Learning (DL) architectures.

The systematic literature reviews analyzing contemporary crop yield prediction studies confirm a massive transition toward algorithmic approaches capable of processing multi-modal environmental datasets without suffering from the curse of dimensionality. This computational evolution has fundamentally transformed agricultural analytics, enabling researchers to move beyond simple correlational studies to develop highly robust, predictive decision-support systems that can anticipate yield fluctuations under unprecedented climatic stress [22].

Initially, early iterations of machine learning models in agriculture frequently treated temporal data in a highly static manner, often relying on arbitrary chronological markers to represent time. Utilizing a generic chronological variable as a numeric predictor frequently introduced structural biases, as the algorithm would erroneously assign mathematical weight to the mere progression of time rather than evaluating the underlying climatic shifts.

Recognizing this fundamental flaw, the methodological landscape rapidly evolved to eliminate static year-based variables in favor of dynamic temporal representations that capture actual sequential dependencies in the agro-ecosystem. Modern algorithmic approaches now predominantly incorporate lagged environmental features, allowing models to mathematically evaluate how a severe weather anomaly or soil moisture deficit in a previous interval actively depresses the current harvest potential. By shifting from chronological constants to dynamic lag-features, these advanced computational models can accurately track the compounding nature of climate shocks across consecutive growing seasons [23].

Building upon these refined temporal structures, the most recent paradigm shift in yield modeling involves the widespread deployment of complex Deep Learning architectures capable of automated feature extraction. Traditional machine learning regressors typically required extensive manual data preprocessing, forcing agronomists to explicitly define which climatic and soil variables were most statistically relevant before running the predictive analysis.

The modern deep neural networks fundamentally bypass this limitation by independently identifying hidden, non-linear correlations within massive, unstructured datasets, ranging from pixel-level satellite imagery to continuous humidity sensor feeds. This autonomous processing capability allows DL models to seamlessly fuse diverse data streams, capturing the intricate environmental interactions that traditional statistical methods historically failed to quantify. Consequently, the continuous evolution of these algorithmic approaches has completely redefined the boundaries of precision agriculture, providing stakeholders with highly dynamic, scalable predictive tools that adapt to escalating environmental uncertainties [24].

2.3.2 Tree-Based Ensemble Methods for Agronomic Predictions

Within the diverse landscape of machine learning algorithms, tree-based collective methods have emerged as the dominant and most effective tools for agronomic predictions. Algorithms such as Random Forest (RF) and eXtreme Gradient Boosting (XGBoost) are particularly favored because they inherently manage the high variance, missing values, and multicollinearity typical of meteorological and soil datasets. For instance, studies explicitly targeting regional cotton yields have demonstrated that RF algorithm can successfully integrate complex, long-term agromet-spectral variables such as growing degree days and standardized precipitation indices while rigorously preventing model overfitting. Beyond raw predictive accuracy, tree-based methods provide crucial diagnostic advantages through their native capacity to calculate built-in feature importance rankings. This computational transparency allows agronomists to systematically evaluate the relative influence of hundreds of interacting variables, mathematically isolating which specific meteorological parameters most aggressively dictate the final harvest. However, to maximize the diagnostic utility of these algorithms in highly volatile regions, researchers must carefully engineer the input variables, explicitly avoiding static chronological markers. Training Random Forest and XGBoost architectures exclusively on engineered lag-features rather than relying on a generic 'Year' predictor ensures that the model learns the true sequential impact of abiotic stress rather than simply memorizing historical timelines. By combining this dynamic temporal modeling with the algorithmic stability of collaborative methods, researchers can successfully transition from basic yield forecasting to the precise, directional identification of regional agricultural constraints [25].

Effective crop yield prediction requires the integration of diverse, multi-source datasets, with meteorological factors like temperature and rainfall, alongside soil properties, serving as the most significant contributors to predictive accuracy. Empirical analysis reveals that these variables do not operate in isolation; rather, their non-linear interactions dictate the final harvest potential, necessitating the

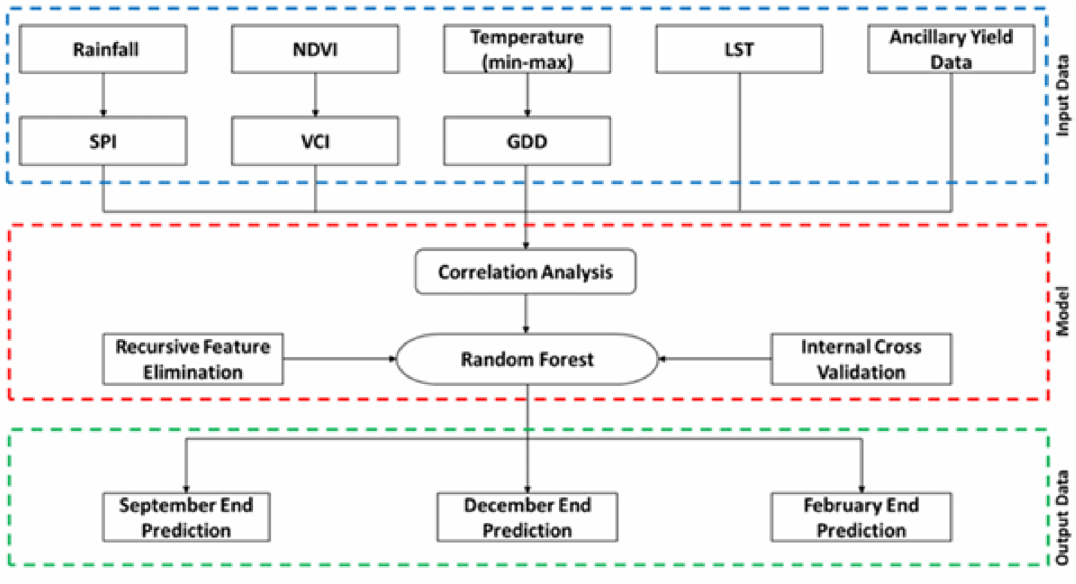


FIGURE 2.7: Methodological framework for cotton yield prediction utilizing the Random Forest algorithm [25]

use of advanced algorithmic frameworks, such as Random Forest and XGBoost, to capture these complex environmental dependencies. Consequently, the performance of predictive systems is heavily dependent on both the quality of historical data and the model's ability to elucidate the relative significance of these critical features [26].

Furthermore, comparative evaluations of various predictive models frequently highlight that XGBoost and Random Forest as superior to both traditional regression and basic artificial neural networks when tasked with disentangling the specific impacts of complex weather parameters like temperature extremes and rainfall distributions. The collaborative nature of these models, which aggregate the predictions of numerous independent decision trees, ensures a high degree of predictive stability, making them exceptionally well-suited for modeling highly weather-dependent crops like cotton [27].

Although individual decision trees provide a highly interpretable structure for mapping agricultural inputs to corresponding yield outputs, they are notoriously susceptible to structural overfitting when exposed to noisy climatic data. To mitigate this inherent vulnerability, collaborative methodologies like Random Forest deploy bootstrap aggregating, simultaneously training hundreds of distinct trees on randomized subsets of the environmental dataset. This advanced bagging technique effectively neutralizes the high variance associated with fluctuating monsoon patterns and erratic thermal spikes, synthesizing a final prediction that is vastly more generalized and robust. Similarly, gradient boosting frameworks such as XGBoost utilize a sequential learning architecture, where each subsequent tree rigorously corrects the predictive residual errors generated by its predecessors. By iteratively minimizing these predictive errors, boosting algorithms achieve unparallel accuracy in mapping complex, non-linear relationships such as the exact thermal threshold where crop growth transitions into catastrophic physiological failure. Beyond baseline statistical validation, evaluative forecast accuracy in highly volatile agricultural environments requires assessing how models handle extreme outlier events such as catastrophic thermal shocks or sudden pest outbreaks. Traditional error metrics inherently average out these critical deviations, frequently masking a model's failure to accurately predict sudden yield collapses during the most sensitive phenological stages. To rigorously test predictive resilience, modern evaluation protocols must scrutinize the Root Mean Squared Error specifically during seasons characterized by acute abiotic stress rather than relying exclusively on long-term historical averages. Furthermore, assessing the true efficacy of dynamic time-series models requires evaluating how effectively engineered lag-features minimize prediction errors across consecutive growing seasons, proving their structural superiority over static chronological variables. By scrutinizing these targeted error distributions, researchers can ensure that the selected algorithmic architecture is mathematically optimized to detect cascading agricultural failures rather than merely smoothing baseline production trends [28].

2.3.3 Comparative Methodologies for Time-Series Forecasting

While tree-based methods work by analyzing cross-sectional environmental data, projecting future agricultural production requires specialized methodologies engineered specifically for time-series forecasting. Historically, the Autoregressive

Integrated Moving Average (ARIMA) model has served as the gold standard for agricultural economists seeking to predict crop acreage, production volumes, and commodity price volatility over extended temporal horizons. For time-series specific models like ARIMA, validation is further extended through statistical criteria including the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), and Mean Absolute Percentage Error (MAPE) to ensure optimal model parsimony and prevent structural overfitting [29].

The Box-Jenkins methodology utilized in ARIMA model is highly effective at identifying non-stationarity in historical cotton production data and applying differencing to establish reliable, mathematically sound baseline forecasts. The fundamental limitation of traditional univariate time-series frameworks is their mathematical inability to simultaneously process multiple interacting environmental covariates alongside historical yield records. While autoregressive models provide excellent mathematical smoothing for baseline economic trends, they cannot proactively account for sudden, unprecedented climatic anomalies that abruptly alter expected harvest outcomes. To overcome these structural deficiencies, agricultural data scientists are increasingly deploying multivariate machine learning frameworks capable of synthesizing historical production sequences with complex meteorological arrays. Comparative analyses consistently demonstrate that integrating localized weather variables, such as heat stress indices and humidity fluctuations, significantly enhance the predictive accuracy of these advanced temporal models. By benchmarking these comprehensive, multi-dimensional models against traditional baseline techniques, researchers can definitively identify the most robust algorithmic architecture for navigating the escalating volatility of regional agricultural zones [30].

However, modern agricultural forecasting increasingly demands the integration of dynamic climate change variables into these historical time-series projections, a task where traditional univariate ARIMA models often face limitations. Consequently, contemporary research emphasizes comparative methodologies, benchmarking classic time-series models against advanced machine learning regressors (such as Decision Trees and Random Forests) to accurately forecast future cotton yields under shifting climatic and economic constraints [21].

Furthermore, the successful application of these advanced comparative methodologies fundamentally depends on how the temporal data is structurally engineered prior to algorithmic training. In standard forecasting models, researchers frequently utilize the chronological year as a primary numeric predictor, which inadvertently forces the algorithm to learn an artificial linear progression rather than actual agro-ecological dependencies. To rectify this critical methodological flaw, contemporary time-series evaluations strictly replace static chronological markers with dynamic lag-features that capture the true sequential impact of environmental stressors across consecutive growing seasons. By training complex machine learning regressors exclusively on these engineered temporal lags, predictive models can accurately map how a severe thermal shock in one specific interval continues to depress crop viability in subsequent phases.

This deliberate shift toward lag-integrated modeling ensures that comparative forecasting outputs reflect authentic, data driven climate vulnerability rather than merely extrapolating historical timelines into the future [31]. Recent advancements have further demonstrated the efficacy of hybrid Long Short-Term Memory (LSTM) approaches and collaborative deep learning architectures to successfully capture the non-linear dynamics of weather-dependent crop yields in semi-arid environments [32].

2.3.4 Evaluation Metrics for Forecast Accuracy

The reliability and operational viability of any predictive agricultural model hinge entirely upon the rigorous application of standardized evaluation metrics. In the context of machine learning regression and algorithmic forecasting, researchers universally rely on metrics such as the Coefficient of Determination (R-Squared), Root

Mean Squared Error (RMSE), and Mean Absolute Error (MAE) to quantify algorithmic precision and prediction error [33]. A critical challenge highlighted in recent literature is that while complex deep learning models may achieve marginally superior R-Squared scores, they often require exponentially higher computational costs and sacrifice biological transparency. Therefore, the selection of an appro-

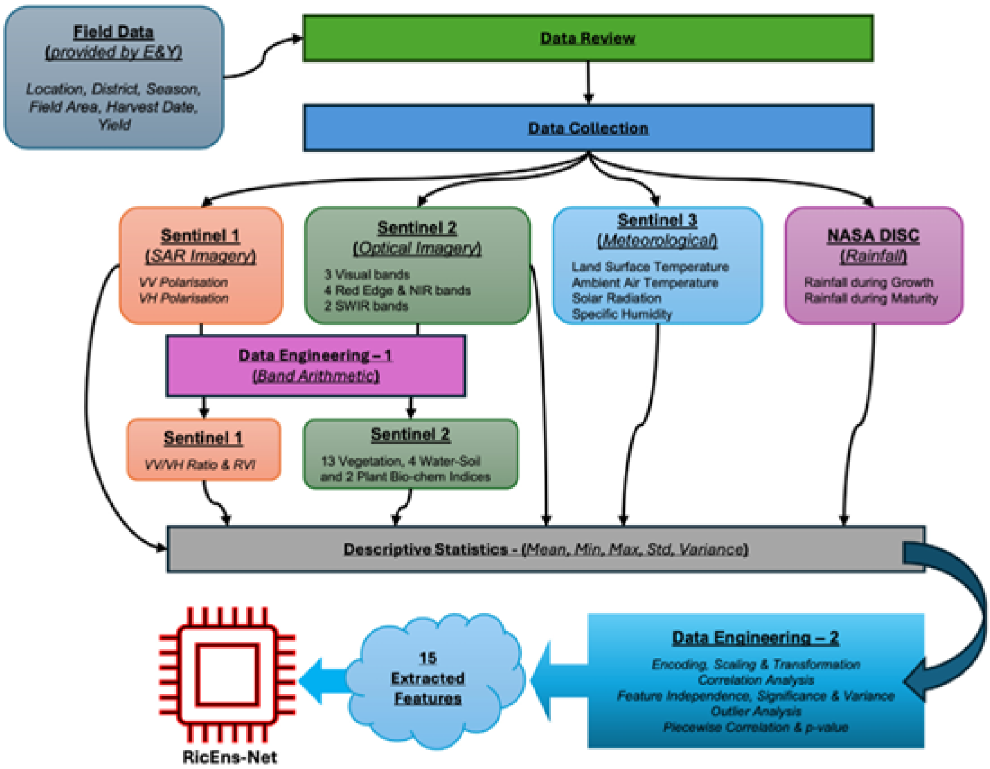


FIGURE 2.8: Integrated Multi-Source Data Acquisition and Feature Engineering Pipeline for the RicEns-Net Forecasting Framework [34]

priate forecasting model must strike a deliberate balance between achieving high statistical accuracy and maintaining the practical interpretability required to inform real-world agronomic interventions. The data pipeline shown below establishes a systematic approach to agricultural forecasting by integrating field-level observations with satellite derived remote sensing and meteorological datasets. This multi-stage process utilizes band arithmetic to transform raw imagery into meaningful biophysical indices, which are then refined through rigorous statistical procedures such as correlation analysis and outlier detection to ensure feature significance. Ultimately, this framework compresses diverse environmental inputs into a curated set of 15 high-impact features, providing a reliable foundation for predictive modeling that effectively filters data noise to focus on variables actively driving agricultural productivity [34].

2.4 Explainability and Feature Identification in Agronomic Models

2.4.1 The Black Box Challenge in Agricultural Machine Learning

Despite the unprecedented predictive accuracy achieved by advanced machine learning models, their adoption in practical agronomy is severely hindered by the pervasive "black box" problem. Complex algorithms, particularly deep neural networks and extreme gradient boosters, transform highly dimensional environmental data into precise yield forecasts through intricate, mathematically opaque internal pathways. Consequently, while these models can accurately project crop losses under shifting climatic conditions, they inherently fail to explain why or how specific agro-environmental parameters drive those predictions [9]. This lack of transparency presents a critical barrier for agricultural stakeholders, as farmers and policymakers cannot design actionable climate adaptation strategies or optimize input management without understanding the physical mechanisms triggering the yield decline. Recognizing this severe limitation, contemporary agricultural research emphasizes that high predictive accuracy must no longer be the sole benchmark of success; models must simultaneously offer mechanistic interpretability to be practically viable and trustworthy [10].

The operational utility of complex forecasting models is fundamentally compromised when their internal decision-making processes remain entirely obscured from the end-user. For example, a deep learning architecture might flawlessly predict a catastrophic harvest failure for a specific farming district based on a massive

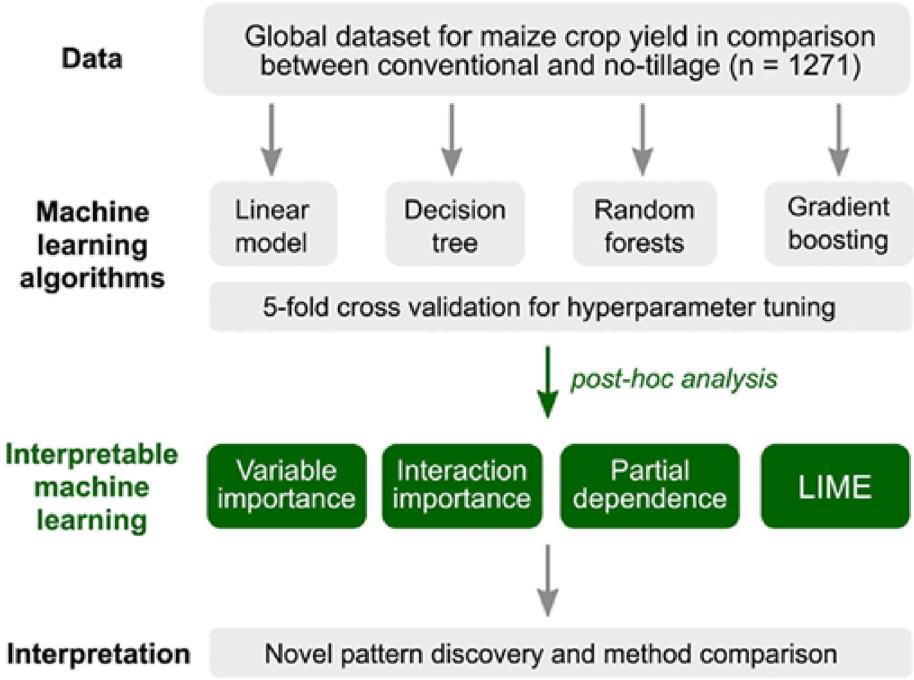


FIGURE 2.9: Conceptual framework contrasting traditional black-box models with Explainable AI in agricultural data analysis [10]

matrix of historical weather sensor data and satellite imagery. However, without the capacity to deconstruct this mathematical prediction, agronomists are left guessing whether the impending failure is primarily driven by a localized soil moisture deficit, an acute thermal shock during flowering, or an undetected pest outbreak. This severe diagnostic ambiguity renders even the most statistically accurate algorithms completely inadequate for formulating targeted, preventive field interventions prior to the actual crop collapse. Therefore, the transition from theoretical data science to applied agronomy necessitates computational frameworks that prioritize biological transparency over abstract mathematical precision [35].

2.4.2 Explainable AI and Parametric Identification Techniques

Precision agriculture frameworks leverage Artificial Intelligence (AI) to optimize crop management by synthesizing high-dimensional, multi-source datasets that encompass meteorological, soil, and field-level variables. Through rigorous data engineering including correlation analysis, outlier detection, and the systematic extraction of high significance features AI models can provide precise, real-time insights into crop health and resource requirements. This data-driven approach facilitates the identification of critical parameters that govern crop productivity, thereby enabling more efficient decision-making processes that improve yield while minimizing resource inputs and environmental impact [36].

The integration of Explainable AI (XAI) is critical for overcoming the 'black-box' nature of traditional machine learning models in agricultural research, as it provides transparency into how internal decision-making processes influence predictive outputs. By employing techniques such as the Shapley Additive Explanations (SHAP), researchers can deconstruct model predictions to quantify the specific directional impact of individual driving factors, effectively distinguishing between variables that exacerbate environmental stress and those that contribute to stability. This level of interpretability is essential for transforming complex algorithmic outputs into actionable diagnostic insights for regional agricultural management [37].

Furthermore, techniques like Permutation Feature Importance are extensively utilized within Random Forest architectures to evaluate model sensitivity by measuring the drop in predictive accuracy when a targeted environmental variable such as maximum temperature or rainfall, is randomized. These parametric identification strategies have successfully demystified multi-model datasets, allowing researchers to isolate critical drivers like morning relative humidity, unseasonal precipitation, and specific soil nutrients as the primary stressors within localized agricultural zones [38].

Additionally, recent advancements have introduced "glass-box" models such as the Explainable Boosting Machine (EBM), which possess inherent, intrinsic interpretability, bypassing the need for post-hoc explanation tools altogether while maintaining highly competitive predictive accuracy [39]. Specifically, the application of post-hoc explanation methods like SHAP and LIME has been pivotal in demystifying deep learning models, allowing for robust feature selection and the interpretable analysis of climate impacts on agricultural yields [40].

2.4.3 Moving from Predictive Correlation to Directional Causality

While current Explainable AI frameworks excel at ranking the relative importance of environmental parameters, they frequently fall short in establishing actionable, directional causality regarding crop degradation. Standard feature importance metrics such as those generated by traditional Random Forest permutation, successfully quantify the magnitude of a variable's impact on the model but often obscure whether that impact actively enhances the yield or detrimentally pulls it down.

In the context of the severe cotton yield decline observed in regions like Bahawalpur, identifying and claiming only "pesticide usage" or "temperature" as a highly important variable is insufficient; researchers must determine the specific harmful threshold and directional trajectory of these inputs.

Consequently, there is a critical methodological gap necessitating the integration of directional weighting mechanisms such as negative correlation weighting directly into feature importance calculations to isolate strictly detrimental factors. By advancing from basic predictive correlation to decline-focused interpretability. This refined parametric approach ensures that only the agro-climatic variables actively causing harm are highlighted, providing a precise diagnostic tool for policy intervention and farm-level mitigation.

Advanced iterations of these interpretable models are now being used to evaluate the specific directional impact of abiotic stressors, ensuring that interventions target variables that actively harm crop development rather than simply correlating with general trends [9].

2.5 Emerging Technologies and Spatial Data Integration

2.5.1 Earth Observation and Remote Sensing in Crop Modeling

The integration of multi-spectral Earth Observation (EO) data particularly from the Sentinel-2 satellite has revolutionized crop monitoring by providing high-resolution, time-series data that capture essential biophysical indicators such as the Normalized Difference Vegetation Index (NDVI). These spatial datasets allow for a granular assessment of crop health, effectively mapping the heterogeneous conditions of soil and vegetation that drive yield variability across large-scale farming regions. By coupling these indices with advanced deep learning architectures, such as Convolutional Neural Networks (CNNs), researchers can autonomously identify patterns in crop development and soil interaction, providing a transparent basis for informed agricultural decision-making [41]. Furthermore, the synthesis of multi-source data including synthetic aperture radar (SAR), optical imagery, and meteorological parameters enables a multidimensional understanding of agricultural systems, which is crucial for identifying the specific factors responsible for yield suppression. Remote sensing applications now extend beyond mere descriptive monitoring to encompass sophisticated feature engineering, where biophysical parameters are transformed into dynamic, sequential datasets suitable for predictive modeling. This multi-modal approach mitigates the limitations of isolated field observations by providing a synoptic view of regional stressors, ultimately supporting the diagnosis of complex agricultural collapse in areas like the Bahawalpur division [42]. By integrating these spatial vegetation indices with complex meteorological arrays and stratified soil properties, researchers have successfully constructed highly accurate, multi-modal data fusion networks capable of mapping field-level yield variations [43]. The adoption of advanced Earth Observation (EO) technologies is essential for modernizing agricultural monitoring, as satellite-based remote sensing provides high-resolution, multi-temporal data critical for mapping crop health and field-level dynamics. By integrating multi-sensor data such as Sentinel-1 SAR, Sentinel-2 optical imagery, and Landsat EVI composites with high-resolution hydrologic and soil models, researchers can generate comprehensive, field-scale datasets that significantly improve the precision of yield forecasting. This multi-modal integration allows for the continuous tracking of phenological changes and environmental stressors, providing the empirical foundation needed to diagnose and mitigate the systemic factors suppressing cotton yields [44]. Beyond data acquisition, the efficacy of spatial modeling relies on sophisticated feature engineering and deep learning architectures that can process complex, unstructured temporal data. Techniques such as Savitzky-Golay filtering are employed to smooth noisy time-series signals from satellite imagery, while CNN-based structures and attention mechanisms, such as Convolutional Self-Attention (CSA), are utilized to extract key spatial features, including vegetation indices and texture patterns. The deployment of hybrid deep learning architectures such as the R2U-Net-AgriFocus model further enhances predictive capabilities by capturing both spatial dependencies and long-term temporal trends, ultimately facilitating a diagnostic approach that prioritizes actionable insights for agricultural planning [45]. Advancements in Deep Learning (DL) have significantly improved the precision of crop yield forecasting from high-resolution satellite imagery; however, the 'black-box' nature of these models often obscures the underlying decision-making processes, limiting their operational dependability. To address this, Explainable Artificial Intelligence (XAI) techniques, such as Layerwise Relevance Propagation (LRP) and perturbation analysis, have been introduced to validate that predictive models are leveraging the correct spatial information specifically focusing on crop fields rather than auxiliary land uses. This transparency is fundamental for establishing trust in automated agricultural systems, ensuring that models can be robustly applied to future datasets for sustainable agricultural planning [46]. Predicting the water status of crops like cotton necessitates the integration of multispectral data with sophisticated machine learning algorithms capable of detecting localized environmental stressors. By employing techniques such as the SHapley

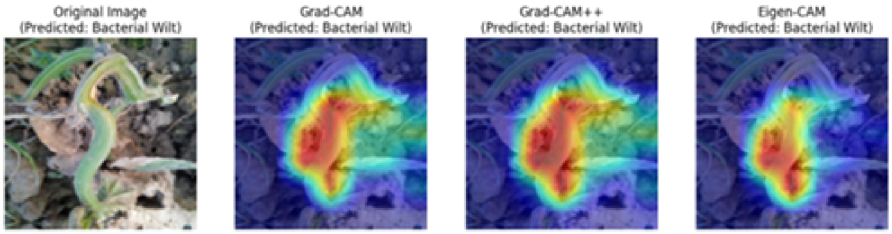
Additive exPlanations (SHAP) method, researchers can quantify the influence of individual spectral bands on the predicted water status, thereby identifying specific bands, such as the blue and red-edge regions, that serve as critical predictors of plant health. Such interpretability-focused frameworks allow for a mechanistic understanding of how environmental variables drive crop responses, ultimately supporting the development of more efficient, climate-smart irrigation strategies [47]. This multi-layered approach includes integrating Sentinel-2 satellite imagery and UAV-based multispectral imaging for mid-season crop yield estimation and the early detection of foliar stress [48].

2.5.2 Deep Learning for Plant Disease and Phenotyping

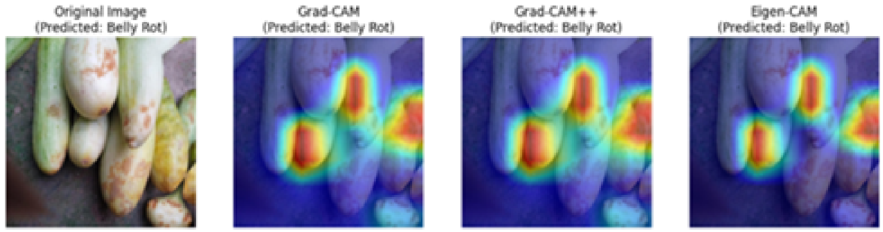
Beyond broad spatial forecasting, computational agriculture has aggressively expanded into microscopic phenotyping and automated disease diagnostics through the application of advanced computer vision. Recognizing that pest infestations and foliar diseases are primary drivers of cotton yield decline, researchers have transitioned from manual field scouting to deploying deep Convolutional Neural Networks (CNNs) capable of instantly classifying complex leaf damage [49]. The true diagnostic potential of automated phenotyping is fully realized when these isolated microscopic visual assessments are dynamically integrated with broader meteorological and chronological datasets. Rather than treating a diagnosed disease outbreak as an isolated biological event, advanced modeling frameworks utilize sequential image processing to mathematically track the progression of foliar damage across consecutive phenological stages. By converting these continuous visual diagnostic assessments into dynamic lag-features, machine learning algorithms can accurately correlate a specific mid-season pest infestation with localized humidity spikes that occurred in previous temporal windows. This temporal integration ensures that the predictive model evaluates the plant's health trajectory not as a static snapshot, but as a compounding sequence of interrelated environmental and biological shocks. Consequently, combining deep learning disease diagnostics with temporally engineered weather data provides the precise, multi-dimensional analytical framework required to actively mitigate the compounding yield crisis [50].

These computer vision frameworks utilize intricate feature extraction methodologies such as Gabor Wavelet filters, texture analysis, and residual bottlenecks to accurately identify the visual signatures of severe agricultural threats like Bacterial Blight, Grey Mildew, and Alternaria [52]. Extensive comparative analyses confirm that deep learning networks overwhelmingly outperform traditional machine learning classifiers when diagnosing both organic and non-organic crop diseases from high-resolution field imagery [53]. By integrating these diagnostic image-processing tools with explainable visualization techniques like Grad-CAM, researchers can isolate the exact morphological stress signals on the plant, providing an early warning system that is critical for mitigating localized harvest failures.

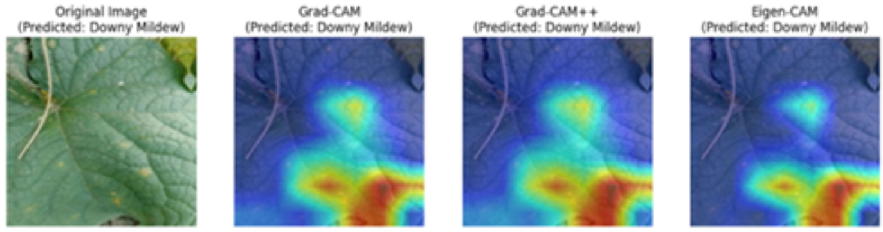
Figure 2.10 demonstrates how Explainable Artificial Intelligence (XAI) techniques, including Grad-CAM, Grad-CAM++, and Eigen-CAM, visually identify the regions that contribute most to model predictions, thereby improving transparency and interpretability. Such visual explanations enable researchers to validate model decisions and enhance user confidence by highlighting the features responsible for classification outcomes. Similarly, the present study emphasizes model interpretability by identifying the most influential agronomic and climatic factors affecting cotton yield through explainable machine learning techniques rather than relying solely on black-box predictions [51]. Automated mapping of crop health using high-resolution Earth Observation data coupled with convolutional neural networks has significantly improved the speed and accuracy of these localized disease diagnostics [54]. While standard Convolutional Neural Networks provide exceptional accuracy in highly controlled laboratory environments, their diagnostic reliability often degrades when deployed under the variable lighting and complex background conditions typical of actual agricultural fields. To overcome these real-world environmental noises, researchers are increasingly utilizing advanced data augmentation techniques and hybrid neural architectures to significantly enhance



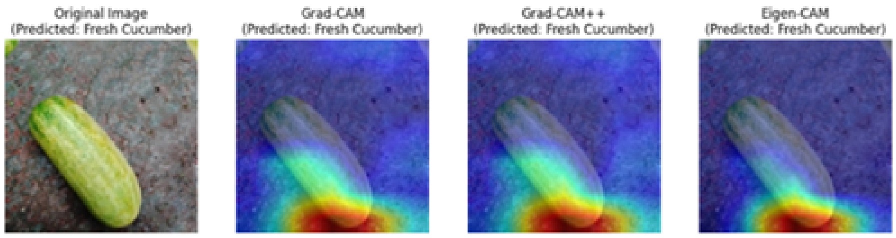
(a) Grad-CAM, Grad-CAM++ and Eigen-CAM visualization for Bacterial Wilt Disease in Cucumber.



(b) Grad-CAM, Grad-CAM++ and Eigen-CAM visualization for Belly Rot Disease in Cucumber.



(c) Grad-CAM, Grad-CAM++ and Eigen-CAM visualization for Downy Mildew Disease in Cucumber.



(d) Grad-CAM, Grad-CAM++ and Eigen-CAM visualization for Fresh Cucumber.

FIGURE 2.10: Grad-CAM, Grad-CAM++ and Eigen-CAM visualizations highlighting areas of interest for various cucumber diseases [51]

the robustness of automated disease identification systems. Furthermore, accurately diagnosing foliar stress in regions like Southern Punjab requires these computer vision models to explicitly distinguish between biological pathogenic damage and abiotic structural harm caused by intense thermal radiation or chemical burns. By training these deep learning frameworks to precisely isolate the unique visual signatures of specific "decline-only" stressors, agronomists can successfully prevent the misdiagnoses that frequently lead to the excessive misapplication of synthetic agrochemicals. Ultimately, refining these microscopic phenotyping tools is an essential computational step in transitioning from generalized crop monitoring to highly targeted, localized agronomic intervention strategies [4].

2.5.3 IoT and Hybrid Optimization Frameworks

The operational deployment of predictive models in precision agriculture is heavily dependent on the Internet of Things (IoT) and the continuous stream of localized environmental data generated by edge devices. By synergizing IoT-enabled field sensors with artificial intelligence, agronomists can establish real-time, climate resilient management systems that dynamically optimize resource allocation such as automated smart irrigation based on live soil moisture readings [55]. Beyond tracking temporal delays, the true utility of hybrid optimization frameworks lies in their mathematical ability to filter the massive influx of IoT data to isolate specific agricultural harm. While edge devices continuously record standard growth-supporting parameters alongside extreme weather anomalies, diagnostic models must be explicitly calibrated to isolate the "decline-only" variables that actively suppress crop viability.

Advanced neurosymbolic architectures and federated learning paradigms achieve this by rigorously applying negative correlation weighting, successfully separating the acute thermal spikes that induce boll shedding from harmless baseline temperature fluctuations. This highly targeted algorithmic filtering ensures that automated smart irrigation and input management systems react exclusively to genuine, localized environmental threats rather than overcompensating for gentle microclimatic shifts. Ultimately, seamlessly integrating real-time IoT surveillance with these highly diagnostic hybrid optimization models provides the exact technological architecture required to actively reverse the systemic yield collapse [56].

The sheer volume of continuous, high-frequency data generated by distributed IoT sensor networks necessitates advanced temporal processing to extract meaningful agronomic insights. Traditional analytical methods often aggregate this continuous sensor data into arbitrary chronological averages, which inadvertently obscures the acute, short-term microclimatic shocks that precipitate physiological crop failure.

To accurately reflect the plant's biological reality, modern predictive frameworks must systematically engineer this IoT data into dynamic lag features, perfectly aligning historical soil moisture or humidity deficits with their subsequent impact on future phenological stages.

By utilizing these dynamic temporal delays instead of generic chronological markers, hybrid algorithms can trace the exact compounding trajectory of an environmental stressor from initial detection at the field edge to final yield degradation. Consequently, this sophisticated temporal integration transforms raw, localized sensor feeds into an actionable, predictive timeline that empowers agronomists to intervene before cumulative environmental stress irreparably damages the harvest [57].

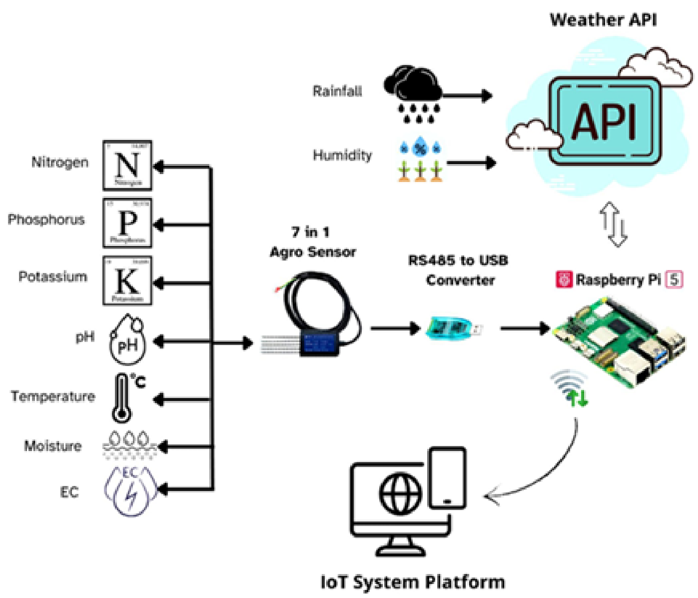


FIGURE 2.11: Operational architecture of an IoT-enabled agricultural monitoring system, illustrating the integration of 7-in-1 agro-sensors and weather API data for real-time field status assessment [57]

To process the immense complexity of this continuous data, the literature reveals a significant trend toward hybridizing base algorithms, utilizing techniques like the Levy flight-enhanced Coati Optimization Algorithm or neuro-symbolic integrations to fine-tune the hyper-parameters of Artificial Neural Networks [58]. The rapid evolution of agricultural technology is increasingly defined by the synergy between distributed Internet of Things (IoT) sensor networks and advanced computational frameworks.

The integration of real-time data analysis combining local weather forecasts with historical crop patterns allows for the development of "weather-informed" predictive systems that significantly improve decision-making accuracy. By moving beyond traditional, isolated statistical models, this IoT-enabled approach provides the continuous, granular monitoring necessary to manage the unpredictable environmental stressors that currently dominate cotton production in vulnerable regions [59]. Recent research highlights the superiority of hybrid models, which combine deterministic historical datasets with real-time, high-frequency sensor inputs to improve predictive stability.

The complex agricultural systems require robust deep neural networks (DNNs) that incorporate advanced feature engineering such as Growing Degree Days (GDD) and extreme weather indices to account for the non-linear relationships between climate and yield. By leveraging these hybrid optimization strategies, agricultural systems can better simulate real-world conditions, effectively mitigating the reliability issues that historically plagued simple, univariate forecasting methods [60].

To address the critical challenges of data privacy and localized model training, the FL-AGRN model introduces a distributed framework that integrates attention-based Graph Neural Networks (GNNs) with Recurrent Neural Networks (RNNs). By utilizing the Federated Gaussian Average (FedGAvg) approach, this model enables multiple agricultural clients to collaborate on global yield predictions without sharing sensitive local data, effectively reducing communication overhead and ensuring scalability across diverse farming landscapes [61].

The development of robust predictive tools increasingly relies on hybrid architectures that synthesize disparate data sources into a unified analytical workflow. Hybrid modeling specifically the integration of machine learning algorithms with process-based simulation models reconciles the strengths of data-driven insights with the fundamental principles of plant physiology. This fusion approach allows models to better capture non-linear agricultural dynamics, such as the complex interactions between soil moisture, nutrient availability, and climatic variability, which are frequently missed by traditional, isolated predictive techniques [62].

The integration of real-time sensor data and machine learning is rapidly transforming agricultural decision-making by enabling precise, actionable forecasting. The interactive, web-based systems employing Random Forest algorithms can empower farmers to predict yields based on parameters like rainfall, humidity, and soil moisture, thereby optimizing market and storage strategies before cultivation even begins.

These frameworks leverage data mining to convert multifaceted environmental observations into summarized, intelligent insights, providing a technological solution to the degradation of seasonal climatic stability and food insecurity [63]. The integration of Internet of Things (IoT) platforms with machine learning frameworks is revolutionizing how we optimize high-performance materials. The development of robust bio-HFRP composites requires managing extensive experimental data across diverse stacking configurations and impact energy levels.

By utilizing IoT-enabled testing environments and automated data collection, researchers can build comprehensive databases that allow for the optimization of resource-intensive testing cycles, significantly reducing the time required to identify the most resilient material layups [64].

The complexity of bio-hybrid composite behavior, particularly under low-velocity impact, necessitates hybrid optimization frameworks that can bridge experimental observations with predictive accuracy. Recent research demonstrates that integrating tree-based algorithms, such as Decision Trees (DT), with neural network structures (DNN and RNN), allows for a multi-layered analysis of intricate variables like peak impact force and damage extension.

This hybrid optimization approach not only enhances the predictive fidelity of material response under varied energy loadings but also provides a systematic methodology for hyperparameter tuning, which is essential for ensuring that predictive models generalize effectively from small experimental datasets to diverse industrial applications [65]. Such predictive analytics and IoT frameworks are particularly vital for optimizing input management and irrigation scheduling under water-scarce conditions.

2.5.4 Field-Level Agronomic Surveys and Socio-Economic Trade-offs

The efficacy of field-level management is often dictated by the socio-economic context of the farm, including the distance of fields from homesteads and the frequency of organic resource application. Findings suggests that maize grain yields in northern Tanzania were significantly reduced by increasing distance from the homestead and insufficient manure application frequency. These results illustrate that socio-economic trade-offs where farmers may prioritize fields closer to the homestead due to labor and resource constraints lead to persistent soil fertility degradation in remote plots, a critical barrier to arresting long-term productivity decline [66].

To accurately identify the drivers of agricultural productivity, researchers must employ field-level agronomic surveys that go beyond generalized climatic data to capture micro-level management constraints. Kihara et al. demonstrate that within-field yield variability is heavily influenced by factors such as plant density, field slope, variety choice, and the period since land conversion. By utilizing regression tree models to analyze these variables, this survey approach provides a cost-effective methodology for identifying yield-limiting management practices, such as sub-optimal plant populations and nutrient mining, which frequently create substantial yield gaps in smallholder systems [67]. For example, studies assessing nitrogen footprints in arid environments reveal that poor fertilizer management actively degrades soil health and limits nutrient transport to cotton bolls, directly contradicting the intended benefits of chemical inputs [68]. Effective agricultural research requires shifting from broad statistical assessments to granular, field-level diagnostics that capture the realities of farm management. Environmental variation in multi-environment trials (MET) is a major constraint in cotton production, necessitating detailed, genotype-specific studies to identify stable and adaptable varieties that can perform consistently under diverse agro-climatic conditions. By analyzing the genotype-environment interaction (GEI) and utilizing both parametric and non-parametric stability measures, this approach provides a robust framework for identifying high-performing genotypes, which is a critical step in addressing the low productivity currently observed in many developing agricultural regions [69].

Agronomic success depends heavily on the interaction between variety choice and the management regime, as cultivars bred for conventional farming often underperform under the constraints of organic or low-input systems. Rempelos et al. demonstrate that varieties bred for organic or low-input sectors characterized by longer straw and higher foliar disease resistance can provide greater stability and comparable yields to conventional varieties when managed with organic protocols. Their findings reveal a complex socio-economic trade-off: while conventional varieties may show higher potential yields under optimized mineral fertilizer and pesticide inputs, they often fail to achieve bread-making quality or maintain stability in cooler, wetter seasons, highlighting the necessity of matching variety selection to the specific socio-economic and agronomic framework of the farm [70].

Field-level agronomic surveys are indispensable for identifying the localized management drivers that dictate yield performance, as evidenced by Kassa et al. in their study of tropical cotton systems. Their research highlights that productivity is often constrained not only by broad climatic factors but by farm-level decisions regarding variety choice, planting timing, and the frequency of manure application. Because current rainfed systems often struggle with low yields necessitating thousands of kilograms of lint per hectare to offset the environmental opportunity costs of land clearing these surveys are critical for helping policymakers and farmers implement management practices (such as crop rotation and integrated pest management) that improve both financial and environmental sustainability [71]. Beyond traditional agronomy, the integration of big data and explainable artificial intelligence (XAI) offers a new paradigm for field-level socio-economic decision support. Xia et al. propose a ”big data-forecasting model-decision support” framework that goes beyond simple point estimation to provide probability-based volatility forecasting. While their work focuses on cotton yarn futures, the framework's use of explainable techniques like LassoNet and SHAP to identify influencing factors provides a template for field-level research; such methods can allow farmers and policymakers to quantify how various socio-economic and input factors such as price volatility, market indicators, and management choices interact to drive farm-level economic outcomes [72].

2.6 Tabular Analysis of Contributing Parameters

A comprehensive evaluation of the existing literature reveals a multitude of interacting agro-environmental parameters that collectively govern cotton crop development and ultimate yield realization. While predictive machine learning models often utilize dozens of input variables to generate long-term forecasts, a targeted diagnostic analysis requires the precise isolation of specific factors that have been empirically proven to induce physiological or biological stress.

To effectively map the multidimensional nature of the cotton yield decline in Pakistan, it is imperative to systematically categorize these contributing parameters into distinct climatic and agronomic domains. The following tabular analysis synthesizes the most critical environmental stressors, biological threats, and management inefficiencies identified across the reviewed academic studies. By explicitly outlining the directional impact of each parameter such as how thermal extremes suppress boll retention or how humidity spikes trigger pest infestations, this framework establishes the baseline variables required for the subsequent diagnostic modeling of the Bahawalpur division.

Table 2.1: Synthesized agronomic and climatic parameters contributing to cotton yield decline

Parameter Category	**Specific Parameter / Variable**	**Directional Impact & Stress Mechanism on Cotton Yield**	**References**
Climatic Stressors	Extreme Daily Maximums	Induces immediate reproductive failure, flower abscission, and asynchronous organ development if temperatures exceed 35C to 43C.	[7, 15]
Climatic Stressors	Persistent Nighttime Warming	Restricts essential carbohydrate supply and depletes energy pools through enhanced nocturnal plant respiration.	[7, 13]
Climatic Stressors	Relative Humidity Unseasonal Rainfall	High humidity coupled with unseasonal rain disrupts pollination mechanics and acts as a primary catalyst for insect pest proliferation.	[5, 73]
Climatic Stressors	Evaporation Rate Wind Speed	High evaporation exacerbates water deficits causing boll shedding, while strong erratic winds physically damage the plant canopy.	[15, 18]
Agronomic / Biological	Pest Infestations (Whitefly, Bollworm, Jassids)	Direct biological destruction of foliage and fruiting bodies, heavily exacerbated by shifting climatic windows and humidity spikes.	[5, 52, 53]
Agronomic / Biological	Input Inefficiencies (Pesticides Fertilizers)	Panicked, excessive chemical application yields negative marginal returns, increases production costs, and degrades long-term soil health.	[2, 6, 68]
Agronomic / Biological	Sowing Date Crop Density Misalignment	Failure to adapt planting schedules to climate-altered seasonal windows results in compressed phenological stages and suboptimal growth.	[11, 20]

The agronomic and climatic parameters presented in the above Table 2.1 clearly illustrate that the drivers of cotton yield decline do not operate in isolated silos, but rather function as a highly interconnected network of compounding stressors. For example, the literature demonstrates that anomalous spikes in relative humidity directly catalyze the proliferation of biological pests like whiteflies, which in turn forces farmers to implement economically inefficient and chemically degrading pesticide regimes. Similarly, extreme thermal shocks not only induce immediate reproductive failure through flower abscission but also worsen the region's underlying soil moisture deficits, severely compounding the crop's physiological water stress. Although, individual studies have successfully documented the destructive nature of these specific parameters, current research predominantly evaluates them either through isolated field experiments or broad, black-box predictive algorithms. Therefore, translating these well-documented variables into an actionable, localized diagnostic framework requires a novel methodological approach capable of simultaneously weighting both the climatic and agronomic parameters according to their directional harm.

2.7 Summary of Literature Review

The comprehensive review of the literature establishes that the prominent decline in Pakistan's cotton production is a multifaceted crisis driven by the intricate interplay of climatic and agronomic stressors. Historical production data vividly illustrates a systemic collapse from peak yields of over 14 million bales down to a precarious 5 to 6 million, with the semi-arid Southern Punjab region acting as the primary epicenter of this agricultural degradation. Scientific investigations confirm that the crop is exceptionally vulnerable during its critical July-to-September phenological window, where thermal extremes, erratic rainfall, and high humidity directly suppress boll retention and catalyze devastating pest outbreaks like whitefly and bollworm. Furthermore, the literature highlights that farmer responses to these climate-induced biological threats such as the excessive, uncalibrated application of chemical pesticides and fertilizers often exacerbate the problem by diminishing soil health and reducing long-term economic viability. Consequently, it is evident that the crisis in regions like Bahawalpur cannot be attributed to a single isolated variable, but rather emerges from a compounding cascade of environmental shocks and subsequent management inefficiencies.

To comprehend and anticipate these complex agricultural fluctuations, the methodological landscape has decisively shifted from traditional statistical evaluations toward advanced predictive analytics and machine learning. Traditional time-series models, particularly ARIMA frameworks, have historically provided robust mathematical foundations for forecasting baseline production trends and economic market volatilities over extended temporal horizons. However, modern agronomic research increasingly relies on tree-based collaborative algorithms such as Random Forest and XGBoost, due to their superior capability to process high-dimensional, non-linear environmental datasets without yielding to structural overfitting. While these sophisticated computational models consistently achieve exceptional predictive accuracy in forecasting aggregate crop yields, their inherent mathematical complexity introduces a significant operational barrier known as the "black box" problem. As a result, the literature indicates that prioritizing raw predictive power often sacrifices the biological and agronomic transparency required for stakeholders to actually understand the physical mechanisms driving those algorithmic predictions.

In response to this critical deficit, contemporary research has begun integrating and parametric identification techniques to demystify complex algorithmic outputs. Post-hoc interpretability tools and feature importance metrics such as Random Forest permutation, have successfully enabled data scientists to rank the relative influence of specific environmental variables within predictive crop models. Despite these advancements, a synthesis of the current literature reveals a profound conceptual limitation: existing methodologies excel at identifying which variables are statistically significant, but they generally fail to quantify whether those variables are actively causing directional harm to the crop. The inability to distinguish between an environmental factor that strongly supports yield and one that aggressively pulls it down renders many predictive models practically inadequate for designing targeted, farm-level interventions. Therefore, the literature review underscores the urgent necessity for a novel, diagnostic analytical framework that moves beyond basic predictive correlation to explicitly isolate the directional parameters responsible for agricultural decline.

2.8 Research Gap

Although a substantial body of research exists on crop yield prediction and climate adaptation in agriculture, much of the work remains focused on specific aspects of crop production rather than providing a comprehensive understanding of the factors affecting yield [2, 8, 25]. Many studies have successfully investigated issues such as pest infestations, disease detection through image analysis, or the effects of individual climatic variables; however, these factors are often examined in isolation, making it difficult to capture their combined influence on crop performance [5, 43]. In addition, the increasing use of advanced machine learning and deep learning techniques has significantly improved prediction accuracy, but the reasoning behind model predictions is not always clear [9, 30]. As a result, existing approaches can often forecast yield outcomes effectively, yet they provide limited insight into the underlying causes of reduced productivity [28]. Consequently, it remains challenging to determine whether declining yields are primarily associated with factors such as pesticide effectiveness, changing temperature patterns, soil degradation, or the interaction of multiple environmental and management-related stressors [6, 10, 16].

Chapter 3

Research Methodology

This chapter describes the methods employed to investigate the factors contributing to cotton yield decline in Bahawalpur division and to forecast future production trends. The study adopts a three-parts analytical framework, with each component addressing a distinct research objective. The first component identifies agronomic factors associated with yield decline by combining Random Forest permutation importance with negative correlation weighting. The second component quantifies climatic stress during the critical months of July through September by constructing a Directional Climatic Stress Index that weights the standardized weather anomalies against observed yield drops. The third component assesses and predicts cotton production for 2026 to 2030 using four different models; ARIMA, Linear Regression, Decision Tree, and Random Forest.

Each component draws on different data sources; each selected for its relevance to the specific research question and its availability for the study area. The agronomic analysis uses farmer-level survey data from the Punjab Crop Reporting Service covering the 2021 to 2025 growing seasons. The climatic analysis uses daily meteorological records from the Bahawalpur division meteorological stations for the same period. The forecasting analysis uses the long-term national production dataset from the Karachi Cotton Association spanning 1947 to 2025.

3.1 Research Framework

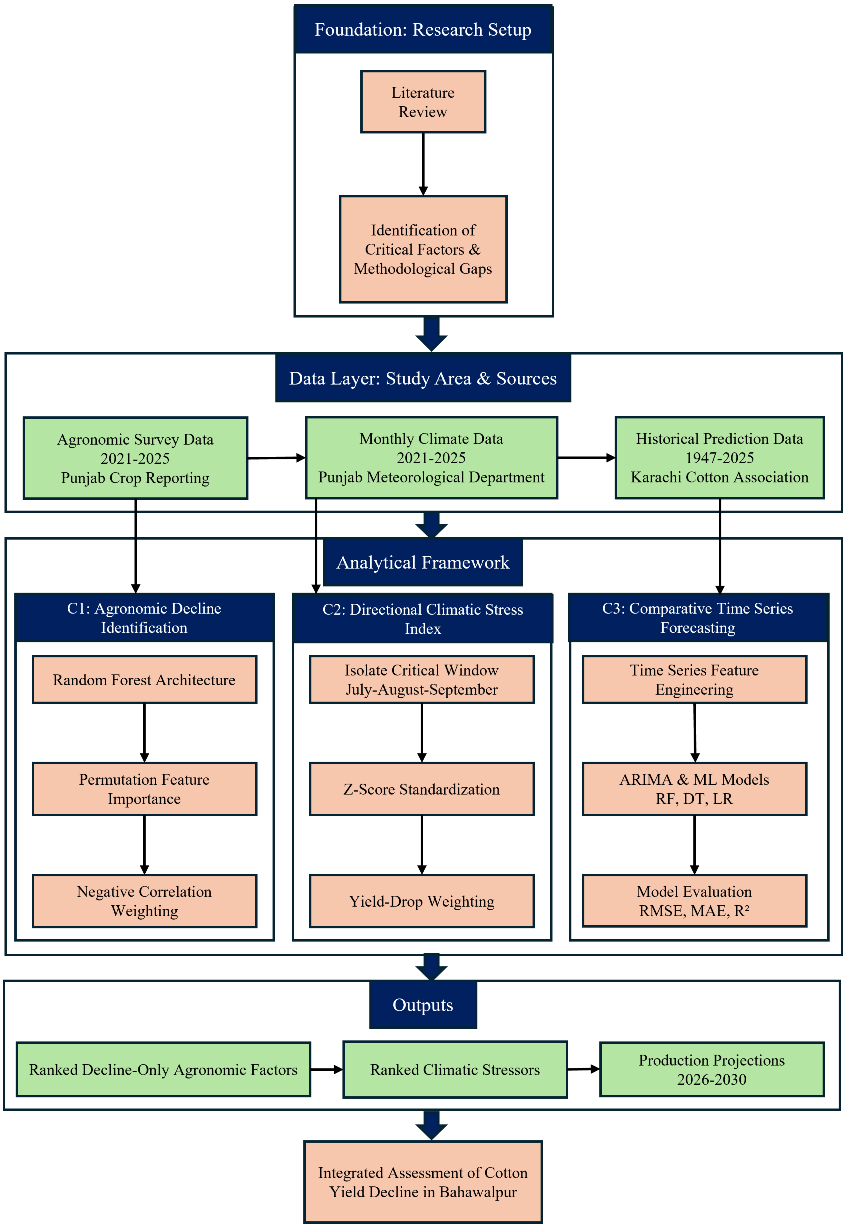


FIGURE 3.1: Conceptual Flowchart of the Research Framework

The research framework comprises three parallel analytical components that converge in an integrated assessment of the cotton yield decline in the Bahawalpur division. This framework is deliberately designed to address the fragmentation identified in the literature review, where studies of agronomic factors, climate impacts, and yield forecasting have largely proceeded in isolation rather than as a cohesive diagnostic system.

The first component systematically identifies the agronomic factors contributing to yield decline. Farmer-level survey data from the Punjab Crop Reporting Service are preprocessed to handle missing values and encode categorical variables. A Random Forest regression model is then trained to predict yield from the full set of agronomic variables. Permutation importance is calculated to measure each variable's baseline contribution to predictive accuracy. Crucially, these importance scores are then multiplied by the absolute value of the Pearson correlation between each variable and the yield, specifically filtering for variables with negative correlations. This novel "decline-only" weighting ensures that the final ranking reflects not just which factors are statistically significant, but which factors are actively pulling yields down.

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The second component isolates and quantifies climatic stress during the critical phenological months of July, August, and September. Daily meteorological data on temperature, rainfall, humidity, and wind speed are aggregated into monthly values for the 2021 to 2025 period. Z-scores are calculated for each climate variable to standardize anomalies relative to the period mean. Biological stress directions are explicitly defined based on established cotton literature; higher temperatures, higher humidity, and lower wind speeds are considered stressful while the rainfall effects are treated as context-dependent. A Directional Climatic Stress Index

(DCSI) is subsequently constructed by multiplying these directional Z-scores by the observed yield drop for each year and summing the results across all climate variables. The third component projects future cotton production for the 2026 to 2030 horizon using a comparative modeling approach. The historical production series from 1947 to 2025 is split into training and test sets, with the final 15 years reserved for testing. Advanced feature engineering is applied to the time-series data to create trend components, dynamic lag variables, and rolling means. An Autoregressive Integrated Moving Average (ARIMA) model is specified utilizing autocorrelation and partial autocorrelation analysis to identify the appropriate mathematical orders. Simultaneously, a Linear Regression model is estimated using trend and cyclical features, while Decision Tree and Random Forest regressors are optimized via cross-validation. The performance of these four distinct models is rigorously evaluated and compared using the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R-Squared).

Ultimately, the outputs of these three components are synthesized into a final integrated assessment. The agronomic analysis generates a ranked hierarchy of decline-contributing farm practices; the climatic analysis provides a parameter-level ranking of environmental stress; and the forecasting analysis delivers robust production projections alongside model comparison metrics. Together, these outputs form a comprehensive, data-driven diagnosis of the active constraints driving cotton yield decline in Bahawalpur, providing a definitive assessment of where regional production is headed.

3.2 Study Area and Data Sources

The Bahawalpur division, located in the semi-arid Southern Punjab region of Pakistan, serves as the primary geographical focus for this research. Historically recognized as a core component of the nation's "cotton belt," the region is characterized by extreme summer temperatures, highly variable monsoon precipitation, and intense pest pressure, making it exceptionally vulnerable to climate induced agricultural degradation.

3.2.1 Data Limitations and Parameter Selection

It is critical to acknowledge that the specific agronomic and climatic variables incorporated into this methodology were strictly dictated by regional data limitations. As highlighted in the literature review, ideal predictive models in precision agriculture often utilize highly granular, continuous parameters such as real-time soil moisture sensor data, solar radiation metrics, precise micro-nutrient tracking, and multi-spectral satellite indices [34]. However, in the context of developing agricultural zones like Bahawalpur, such high-resolution, continuous field level data is practically unavailable.

Consequently, this research utilizes the most robust and reliable data physically obtainable from state and regional departments. Crucially, the specific parameters extracted from these regional datasets were not chosen at random; rather, they were deliberately selected because they directly map to the core agronomic and climatic stressors established in the Literature Review (Table 2.1). By isolating available variables that mirror the theoretical drivers of crop failure such as thermal extremes, humidity induced pest outbreaks, and chemical input inefficiencies; the methodology successfully bridges the gap between theoretical agricultural research and the practical realities of available regional data.

3.2.2 Agronomic Data: Punjab Crop Reporting Service

Working within the aforementioned data constraints, the primary agronomic dataset was acquired from the Punjab Crop Reporting Service (CRS). This dataset consists of farmer level field surveys collected across the Bahawalpur division spanning the 2021 to 2025 growing seasons. While it lacks microscopic soil chemistry data, it provides a comprehensive spectrum of the exact practical interventions and biological threats identified as critical in the literature.

The primary target variable for the predictive modeling is the average yield per acre. The independent predictor variables are categorized into three distinct domains:

i. Binary indicators recording the active presence of primary pests, specifically Bollworm, Whitefly, Mealybug, and other pathogenic attacks. These variables correspond directly to the primary biological threats established in recent agricultural modeling [52].

ii. Continuous numerical variables quantifying farmer interventions, including the application rates of standard bulk fertilizers like Urea and Diammonium Phosphate (DAP), alternative fertilizers, the number of irrigated water cycles, and the frequency of chemical spray applications. These map to the input inefficiencies and panicked chemical applications highlighted in the literature [2, 8].

iii. Categorical features defining the underlying field conditions including the specific cotton cultivar planted (Variety), the broad soil composition (e.g., Soiltype such as Sandy, Mayra or Chikney), the preceding crop rotation, and the application of seed treatments.

During data preprocessing, categorical variables such as soil type and variety are transformed into machine readable formats using one-hot encoding, ensuring the dataset is mathematically optimized for the Random Forest architecture.

3.2.3 Climatic Data: Meteorological Record of Bahawalpur Division

To construct the Directional Climatic Stress Index (DCSI), meteorological data was utilized to quantify the specific environmental constraints acting upon the crop. Because advanced parameters like localized evapotranspiration or canopy temperature are unavailable, daily weather records for the 2021 to 2025 period were extracted from regional meteorological stations situated within the Bahawalpur division. These variables were selected based on the literature review, which identified temperature as the dominant climatic factor affecting cotton yield, the rainfall as another important supplementary water source with complex stage dependent effects, the humidity as a key modifier of pest pressure and disease incidence, and the wind speed as a factor affecting evaporative demand and physical plant damage [15, 18]. The dataset captures continuous measurements of fundamental abiotic parameters because the cotton plant is exceptionally susceptible to physiological failure during its reproductive and boll formation stages. These climatic records were chronologically aggregated into monthly averages, with particular emphasis on July, August, and September, as these months encompass the principal reproductive phase (flowering and early boll development) of cotton in Punjab, Pakistan, during which crop phenology is highly influenced by temperature [74]. This temporal aggregation allows the raw weather data to be transformed into standardized anomaly features (Z-scores) that mathematically map to documented historical heatwaves and unseasonal monsoon spikes in the region.

Temperature is recorded as daily maximum and minimum in degrees Celsius. For the Directional Climatic Stress Index, daily values are aggregated to monthly means for each of the critical months: July, August, and September. The literature indicates that temperatures above 32 to 36 degrees Celsius during flowering and boll formation reduce pollen viability, inhibit fertilization, and increase boll shedding, establishing the biological basis for treating higher temperature as stressful during this window [7, 15]. Rainfall is recorded as daily total precipitation in millimeters. For the index, daily values are summed to monthly totals for July, August, and September. The literature indicates that rainfall effects are stage dependent: moderate rainfall during vegetative stages can benefit crop development by supplementing irrigation, but rainfall during flowering and boll formation can increase pest pressure, interfere with pollination, and promote fungal diseases [5, 18]. The Directional Climatic Stress Index therefore treats rainfall as stressful when it deviates from optimal ranges, with the direction of stress depending on the specific month and the magnitude of deviation.

Humidity is noted as daily relative humidity at morning and afternoon observation times. For the index, daily values are averaged to monthly means for July, August, and September. The literature indicates that high humidity during flowering and boll formation increases vulnerability to pest attack, particularly from whitefly and bollworm, and contributes to flower and boll shedding [5]. Higher humidity is therefore treated as stressful during the July-September window. Wind speed is documented as daily average wind speed in kilometers per hour. For the index, daily values are averaged to monthly means for July, August, and September. The literature indicates that wind speed affects cotton through multiple mechanisms: strong winds can dislodge flowers and small bolls, persistent winds increase evaporative demand and can exacerbate water stress, and wind modifies the canopy microclimate [15, 18]. Lower wind speed is treated as stressful because it reduces air movement through the canopy, increasing humidity and pest pressure, and limits the cooling effect of transpiration.

3.2.4 Yearly Cotton Yield Data from Karachi Cotton Association

While the agronomic and climatic datasets provide a high-resolution, short-term diagnostic view (2021–2025), projecting future regional vulnerabilities requires long term historical context. To facilitate the comparative time series forecasting models (projecting 2026–2030), a macro-level production dataset was sourced from the Karachi Cotton Association (KCA). Data quality is fluctuating, data is not consistent showing ups and downs, as the Karachi Cotton Association has maintained consistent recording procedures over its history [75]. The series is complete with no missing years. The data are provided in tabular format with columns for year and production in thousand bales. This extensive time series dataset spans from 1947 to 2025 and contains the annual aggregate cotton production (measured in standard bales) and total cultivated acreage. Target variable for all forecasting models is production in thousand bales. For model evaluation, the dataset is split into training and test sets, with the final 15 years (2011 to 2025) reserved for testing and the preceding 64 years (1947 to 2005) used for training. This split ensures that model performance is evaluated on the most recent period, including the post-2004 decline, while training on the full range of historical experience. For the purposes of this research, the long-term data provides the necessary statistical depth to evaluate baseline production trends, cyclical market volatility, and stationary behaviors. Prior to algorithmic training, this temporal data undergoes rigorous feature engineering to extract dynamic lag variables and rolling statistical means, ensuring the historical production sequence is properly formatted for evaluation by the Autoregressive Integrated Moving Average (ARIMA) and advanced machine learning models.

3.3 Component 1: Agronomic Decline Identification

The first analytical component of the research framework is designed to transition from standard yield prediction to targeted diagnostic assessment. While traditional agronomic models highlight which variables generally influence crop production, they frequently fail to distinguish between factors that actively support yield and those that cause directional harm. To resolve this, this component introduces a custom parametric identification pipeline utilizing tree-based machine learning, permutation feature extraction, and negative correlation weighting to strictly isolate the “decline-only” parameters.

3.3.1 Random Forest Architecture and Data Preprocessing

Prior to algorithmic training, the raw agronomic dataset undergoes rigorous preprocessing to optimize it for mathematical evaluation. Non-predictive identifiers are removed, and numeric variables (such as fertilizer application rates and pesticide spray frequencies) are structurally cleaned using regular expression (regex) formatting to remove anomalous text characters. Missing numerical values are handled via zero-fill imputation to maintain dataset integrity. Binary biological variables specifically the presence of pests such as Bollworm, Whitefly, and Mealybug are mathematically mapped from categorical text ('Yes/No') into binary integer format (1/0). Furthermore, to prevent the algorithm from inferring artificial ordinality, multi-class categorical variables including Variety, Soiltype, Lastcrop, and Ofertname are transformed via one-hot encoding into distinct binary feature columns. Following preprocessing, a Random Forest Regressor is deployed to map the complex, non-linear relationships between the agronomic inputs and the target variable (Average Yield). The algorithm is configured with a robust architecture of 400 independent decision trees (`n_estimators = 400`). This specific collaborative approach is utilized because it effectively manages the high variance and multicollinearity inherent in complex regional agricultural datasets without succumbing to structural overfitting, an approach strongly supported by literature on regional level modeling [25].

3.3.2 Permutation Feature Importance

To extract the baseline influence of each agronomic parameter, the methodology deliberately bypasses the standard Gini-impurity metrics typically associated with Random Forests, as they can be heavily biased toward continuous variables. Instead, the model utilizes Permutation Feature Importance, a technique rooted in Explainable Artificial Intelligence (XAI). Recent advancements in precision agriculture demonstrate that raw machine learning predictions must be coupled with XAI to extract actual biological drivers [26, 38]. This post-hoc interpretability technique evaluates variable significance by systematically shuffling the data values of a single feature column while holding all other variables constant. The algorithm then measures the corresponding drop in the model's overall predictive accuracy. To ensure statistical stability, this shuffling process is iterated ten times per variable (`n_repeats = 10`). The resulting mean accuracy drop provides a highly accurate baseline metric of "Magnitude of Importance" identifying exactly how heavily the model relies on a specific farm management practice or biological stressor to predict the final crop yield.

3.3.3 Negative Correlation Weighting and Feature Aggregation

While Permutation Importance successfully ranks the magnitude of a variable's impact, it inherently lacks directional causality. A high importance score could indicate a factor that dramatically increases yield (e.g., optimal irrigation) or a factor that catastrophically destroys it (e.g., severe whitefly infestation). The danger of relying solely on standard feature importance without directional context has been explicitly identified as a critical flaw in "black box" agricultural models [9].

To resolve this limitation and isolate the specific parameters driving the agricultural crisis in Bahawalpur division, the baseline permutation scores are synthesized with a directional correlation filter. First, the Pearson correlation coefficient (r) is calculated between each independent feature and the target yield.

Next, a custom mathematical mechanism is applied to generate a unique "Decline Score" for each variable. The equation isolates detrimental factors by multiplying the Random Forest Permutation Importance by the absolute value of the Pearson correlation, exclusively applying this calculation to variables possessing a negative correlation trajectory. If a variable possesses a positive correlation (indicating yield support), its Decline Score is strictly forced to zero.

Because the initial one-hot encoding process naturally fractures parent categorical variables (such as splitting a single Variety column into numerous isolated cultivar columns), their individual importance scores become statistically diluted. To rectify this, a final mathematical aggregation step is executed.

The calculated Decline Scores and Permutation Importances of all corresponding sub-variables are systematically grouped and summed back into their original parent categories. This advanced structural aggregation prevents feature dilution and produces a final, cohesive hierarchy of agronomic variables ranked specifically by their active, directional contribution to the yield collapse.

3.3.4 Longitudinal Application (2021–2025)

A critical limitation of traditional cross-sectional agricultural studies is their tendency to pool multi-year data into a single analytical block. While this increases overall sample size, it completely obscures the temporal evolution of agronomic constraints. To accurately map the shifting dynamics of the selected region (Bahawalpur) yield collapse, the aforementioned analytical pipeline comprising Random Forest training, Permutation Importance extraction, and Negative Correlation Weighting is not executed as a single, static model. Instead, it is systematically deployed on a longitudinal, year-by-year basis. As illustrated in the

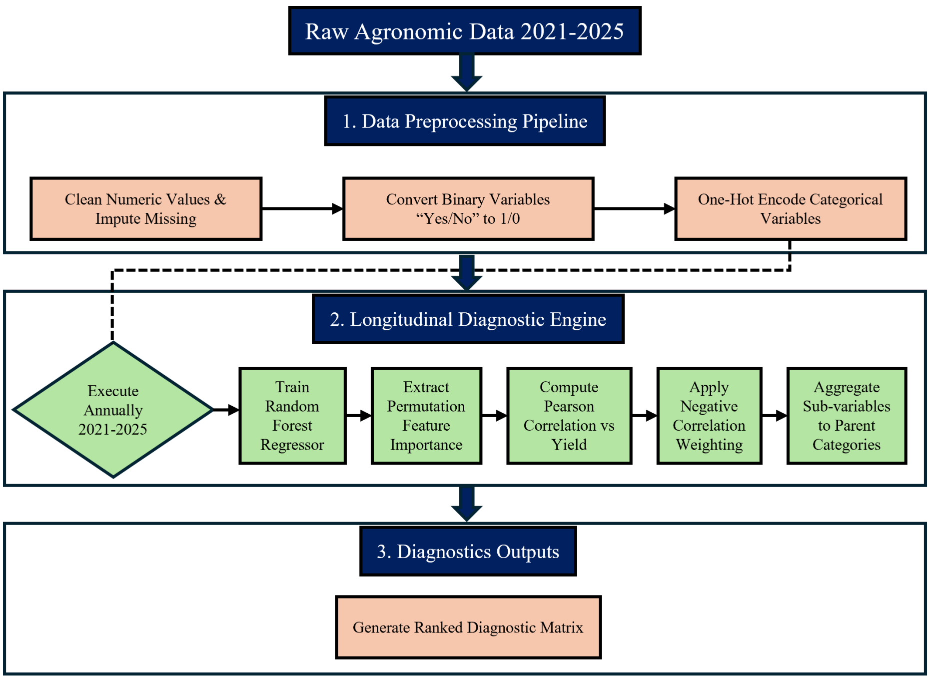

FIGURE 3.2: Framework for diagnostic analysis of agronomic factors

methodological flowchart (Figure 3.2), the entire diagnostic framework is executed independently for each specific growing season from 2021 through 2025. By isolating the datasets chronologically, the methodology calculates distinct, year specific Decline Scores for every agronomic parameter. This allows the research to track the exact trajectory of agricultural stressors over half a decade, identifying whether specific factors (such as uncalibrated pesticide application or specific pest outbreaks) are emerging threats, consistent suppressors, or diminishing variables. The outputs from these five independent annual models are ultimately synthesized into a comparative, multi-year temporal visualization to map the chronological evolution of the crisis.

3.4 Agronomic Diagnostic Framework: Step-by-Step Analysis and Formulation

3.4.1 Step 1: Data Preprocessing

The raw agronomic dataset (2021–2025) is first cleaned to ensure consistency before machine learning analysis.

The preprocessing consists of:

- Missing value imputation
- Numeric value cleaning
- Binary conversion (Yes = 1, No = 0)
- One-hot encoding of categorical variables

For categorical encoding,

$$X_{\text{cat}} \to \begin{cases} 1 & \text{if category exists} \\ 0 & \text{otherwise} \end{cases}$$

where

$$X_{\text{cat}} \text{ represents categorical variables.}$$

3.4.2 Step 2: Random Forest Training

For every year,

$$2021, 2022, \ldots, 2025$$

a Random Forest Regressor is trained. Random Forest prediction is

$$\hat{y} = \frac{1}{T} \sum_{i=1}^{T} h_i(x)$$

where

- T = number of trees
- $h_i(x)$ = prediction of tree i

3.4.3 Step 3: Permutation Feature Importance

For every feature, Prediction accuracy before permutation:

$$Acc_{\text{base}}$$

Prediction accuracy after shuffling feature j:

$$Acc_{\text{perm},j}$$

Permutation importance:

$$PI_j = Acc_{\text{base}} - Acc_{\text{perm},j}$$

Large decrease

$$\downarrow$$

More important feature.

3.4.4 Step 4: Pearson Correlation

Relationship with yield:

$$r_j = \frac{\sum(x_j - \bar{x})(y - \bar{y})}{\sqrt{\sum(x_j - \bar{x})^2 \sum(y - \bar{y})^2}}$$

where

- x_j = feature
- y = yield

3.4.5 Step 5: Negative Correlation Weighting

Your novelty starts here. Only negatively correlated variables should contribute toward decline.

$$W_j = \begin{cases} |r_j|, & r_j < 0 \\ 0, & r_j \geq 0 \end{cases}$$

This removes all beneficial variables.

3.4.6 Step 6: Decline Importance Score

The diagnostic score is

$$DIS_j = PI_j \times W_j$$

where

- PI_j = Permutation Importance
- W_j = Negative Correlation Weight

Large DIS

$$\downarrow$$

Greater contribution toward cotton yield decline.

3.4.7 Step 7: Parent Category Aggregation

If one category contains multiple variables, For example,

$$\text{Irrigation} = \begin{cases} \text{Water Cycle} \\ \text{Water Source} \\ \text{Method} \end{cases}$$

then

$$Score_{\text{Parent}} = \sum_{i=1}^{n} DIS_i$$

3.4.8 Final Output

The agronomic ranking becomes

$$Rank = Sort(DIS_j)$$

Highest score

$$\downarrow$$

Highest decline-causing factor.

3.5 Component 2: Climatic Stress Index Formulation

The second analytical component shifts the focus from farm-level agronomic practices to macro-environmental constraints acting upon the crop. Because regional meteorological data natively consists of smaller, highly aggregated temporal datasets, applying complex machine learning algorithms (such as the Random Forest utilized in Component 1) would lead to mathematical overfitting. A Climatic Stress Index (CSI) was formulated to quantify and rank the abiotic factors influencing cotton yield during its reproductive growth period. Climatic variables were evaluated for July, August, and September, as these months encompass the primary flowering (anthesis) and early boll development stages of cotton in Punjab, Pakistan [7, 74].

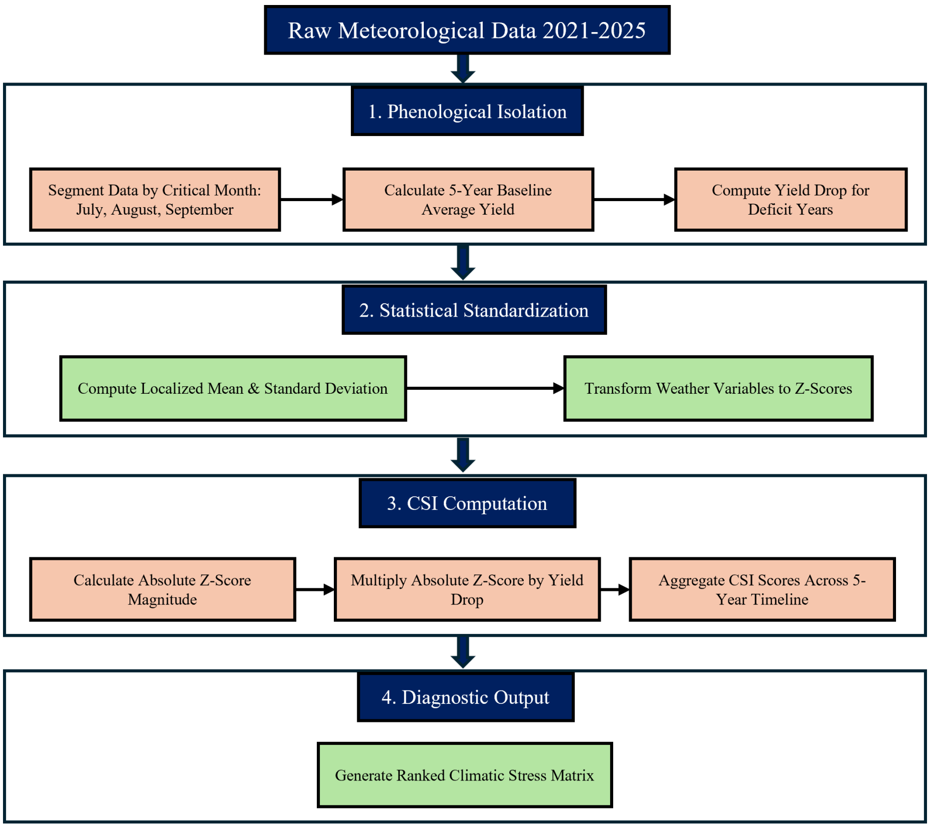

Figure 3.3: Flowchart of the Climatic Stress Index (CSI) Analysis

3.5.1 Phenological Isolation and Yield Drop Quantification

To ensure biological relevance, the analysis is restricted to the critical reproductive and boll-formation window. The meteorological dataset is segmented into three independent, month-specific subsets: July, August, and September [74]. This temporal isolation aligns with established agronomic literature identifying these specific months as the period where the cotton plant is most susceptible to irreversible physiological damage from environmental extremes. The study identifies the period from June to September as the most critical phase of cotton development. Specifically, June–July represents the vegetative growth stage and is described as the "most critical months for harvesting good yield," while August–September corresponds to the flowering and fruit formation stage, which is also considered critical for obtaining good cotton yield [76].

The first computational step involves isolating the years of agricultural failure. For each temporal subset (2021–2025), a baseline average yield ($\bar{Y}$) is calculated. A localized Yield Drop metric is then derived for each specific year (i) by subtracting the actual observed yield (Y_i) from the historical mean.

To strictly isolate conditions associated with agricultural decline, this function is mathematically bounded using a rectified linear unit logic; if a year experienced a yield surplus ($Y_i > \bar{Y}$), the Yield Drop is forced to zero. Thus, the equation focuses exclusively on quantifying the magnitude of loss in deficit years.

3.5.2 Z-Score Standardization of Abiotic Variables

A fundamental challenge in agro-meteorological modeling is dimensional heterogeneity variables are recorded in incompatible units (e.g., rainfall in millimeters, temperature in degrees Celsius, and wind in kilometers per hour). To resolve this, all climatic parameters undergo Z-score standardization. For every climate variable (X) in the month specific dataset, its localized mean (μ) and standard deviation (σ) are computed. Each annual observation (x_i) is then transformed into a standardized Z-score (Z_i) using the standard normalization formula:

$$Z_i = \frac{x_i - \mu}{\sigma} \tag{3.1}$$

This transformation converts all meteorological data into a uniform scale of standard deviations. A high positive or negative Z-score indicates an extreme meteorological anomaly (e.g., a severe heatwave or an unseasonal drought), perfectly formatting the data for cross-variable comparison.

3.5.3 The Climatic Stress Index Calculation

Following standardization, the methodology constructs the Climatic Stress Index (CSI). The core mathematical logic of the CSI asserts that an extreme weather anomaly is only diagnostically relevant if it coincides temporally with a massive collapse in cotton production.

To achieve this, the CSI for each specific weather variable (j) in a given year (i) is calculated by multiplying the absolute magnitude of its standardized anomaly ($|Z_{i,j}|$) by the previously calculated magnitude of crop failure (Yield Drop):

$$CSI_{i,j} = |Z_{i,j}| \times \text{Yield\_Drop}_i \tag{3.2}$$

By utilizing the absolute value of the Z-score, the model successfully captures stress induced by extreme deviations in either direction. This mathematical decision is directly supported by abiotic stress literature, which acknowledges that both extremes such as localized flooding (a high positive Z-score for rainfall) and severe drought (a high negative Z-score) cause catastrophic physiological stress and boll shedding in the cotton plant [18].

3.5.4 Aggregation and Output Matrix

In the final step, the algorithm aggregates the annual stress indices to generate a holistic diagnostic ranking for the entire half decade. The individual CSI scores for each variable (Wind, Rainfall, Temperature, and Humidity) are summed across the 2021–2025 timeline to calculate a total stress score. The variables are then hierarchically sorted in descending order based on their total stress magnitude. This generates a standardized output matrix for each month (July, August, and September). The parameter occupying the Rank 1 position is empirically defined as the most critical climatic stressor driving yield decline for that specific month over the assessed five-year period.

3.6 Climatic Diagnostic Framework: Sequential Analysis and Formulation

3.6.1 Step 1: Phenological Isolation

Only the critical reproductive months

$$\text{July, August, September}$$

are extracted.

3.6.2 Step 2: Baseline Yield

Five-year average:

$$Y_{\text{avg}} = \frac{1}{n}\sum_{i=1}^{n} Y_i$$

where

$$n = 5$$

3.6.3 Step 3: Yield Drop

For each year,

$$YD_i = Y_{\text{avg}} - Y_i$$

If

$$YD < 0$$

then

$$\text{Yield improved}$$

and

$$\text{Stress} = 0$$

3.6.4 Step 4: Standardization

Mean:

$$\mu = \frac{1}{n} \sum x_i$$

Standard deviation:

$$\sigma = \sqrt{\frac{\sum (x_i - \mu)^2}{n}}$$

3.6.5 Step 5: Z-score

For every climatic variable,

$$Z = \frac{x - \mu}{\sigma}$$

3.6.6 Step 6: Absolute Stress

Magnitude only:

$$|Z|$$

Direction is ignored because biological stress may occur due to either unusually high or unusually low values, depending on the variable.

3.6.7 Step 7: Climatic Stress Index

Your CSI equation:

$$CSI = |Z| \times YD$$

where

- $|Z|$ = stress magnitude
- YD = yield deficit

3.6.8 Step 8: Cumulative CSI

Across five years:

$$CSI_{\text{cum}} = \sum_{i=2021}^{2025} CSI_i$$

3.6.9 Step 9: Ranking

$$Rank = Sort(CSI_{\text{cum}})$$

Largest CSI

$$\downarrow$$

Most influential climatic stressor.

3.7 Component 3: Comparative Time - Series Forecasting for 2026–2030

While the diagnostic components of this methodology successfully isolate the localized drivers of historical yield decline, establishing proactive agricultural policy requires anticipating future regional production vulnerabilities. To achieve this, the final analytical component utilizes a macro-level, comparative time-series forecasting framework to project aggregate cotton production up to the year 2030. Given the high volatility and non-stationary nature of historical agricultural production (1947–2025), a multi-model comparative approach was designed. This framework systematically evaluates traditional statistical baselines, regularized linear algorithms, and advanced non-linear machine learning ensembles to guarantee the highest possible predictive accuracy.

3.7.1 Data Transformation and Temporal Feature Engineering

Because predictive machine learning algorithms (such as Random Forest and Linear Regression) cannot natively interpret sequential time dependencies in the same manner as autoregressive statistical models, the one-dimensional historical production series (Y) was expanded through rigorous temporal feature engineering. To stabilize variance and format the series specifically for linear evaluation (Elastic Net), a natural logarithmic transformation was applied to the raw annual production volume:

$$Y_{\log} = \ln(Y) \tag{3.3}$$

Following variance stabilization, a multi-dimensional feature matrix was engineered to capture distinct temporal behaviors, transforming the chronological dataset into a supervised learning format utilized by the machine learning models:

i. Trend Extrapolation Features: Normalized linear and quadratic temporal features were engineered to allow the algorithms to mathematically extrapolate long-term trajectories beyond the existing dataset bounds.

ii. Cyclical Indicators: To capture repeating macro-economic and multi-year climatic patterns, trigonometric transformations (sine and cosine wave functions) were applied to the temporal index to explicitly map 5- and 10-years agricultural cycles.

iii. Short-Term Memory (Lags): Sequential autoregressive lag features (Lags 1 through 5) were generated to capture immediate, year-to-year production dependencies.

iv. Medium-Term Momentum and Smoothing: Rolling statistical means (specifically 3, 5, 7, and 10-year windows) and rolling standard deviations were calculated to smooth anomalous production spikes and identify broader cyclical trends.

v. Volatility and Distance Metrics: Rate of change functions (1- and 2-years percentage changes), acceleration indicators, and the absolute mathematical distance from historical moving averages were calculated to quantify localized temporal volatility.

Prior to model development, the historical cotton production dataset (1947–2025) was transformed into a supervised learning framework through feature engineering. The dataset was subsequently divided into chronologically ordered training and testing subsets to preserve temporal integrity and prevent information leakage. Unlike conventional machine learning applications, time-series forecasting requires that historical observations always precede future observations during model training. Therefore, all forecasting models were trained exclusively using historical observations prior to the testing period, ensuring that future information was never incorporated into model development. This chronological training strategy has been widely recommended for agricultural time-series forecasting and machine learning applications [25, 31, 32].

3.7.2 Model Architectures and Hyperparameter Tuning

To ensure the final forecast is resilient against both overfitting and multicollinearity (a significant risk given the dense feature engineering matrix), four distinct algorithmic architectures were systematically constructed and evaluated. The forecasting framework combines both statistical and machine learning paradigms to provide a comprehensive comparative evaluation. ARIMA was employed as the benchmark statistical forecasting model because of its extensive application in agricultural time-series analysis, while Elastic Net, Decision Tree, and Random Forest represented progressively more sophisticated machine learning architectures capable of modelling linear, non-linear, and ensemble relationships within historical cotton production data [15, 25, 32].

i. Statistical Baseline (ARIMA): An Autoregressive Integrated Moving Average model was deployed to serve as the traditional statistical baseline. Following Augmented Dickey-Fuller (ADF) testing to confirm dataset non-stationarity ($p = 0.6176$), the architecture was configured to an ARIMA (2,1,2) model. Crucially, a linear drift parameter was incorporated to explicitly capture the overarching downward production trend.

ii. Regularized Linear Regression (Elastic Net): To assess linear predictability while controlling for the extreme multicollinearity introduced by the lag and rolling mean features, an Elastic Net Regressor was utilized. This algorithm mathematically integrates both L_1 (Lasso) and L_2 (Ridge) penalties into its loss function, automatically shrinking the coefficients of redundant temporal features to zero.

iii. Non-Linear Baseline (Decision Tree): A standard Decision Tree Regressor was introduced to capture non-linear, hierarchical interactions between the engineered cyclical and momentum features without assuming a rigid mathematical data distribution.

iv. Ensemble Machine Learning (Random Forest): To maximize predictive accuracy and manage high dataset variance, a Random Forest Regressor was deployed. By aggregating the outputs of independent decision trees, this ensemble model inherently resists the noise and overfitting common in complex agricultural datasets.

To optimize the non-linear machine learning algorithms, hyperparameter tuning was executed dynamically. Standard randomized cross-validation cannot be used on temporal data as it causes "data leakage" by utilizing future data to predict the past. Instead, the models were optimized using Grid Search (Grid-Search-CV) and Randomized Search (Randomized-Search-CV) algorithms strictly coupled with Time-Series Cross-Validation (Time-Series-Split utilizing 5 chronological training folds). Through this mathematically rigorous tuning process, the optimal Random Forest architecture was autonomously identified as comprising 75 independent estimators (`n_estimators = 75`), a maximum depth of 8, and a minimum samples split of 2.

3.7.3 Training and Testing Strategy

Since the objective of this research was to forecast future cotton production using historical observations, preserving temporal order during model development was essential. Rather than employing a randomized data split, which may introduce information leakage by allowing future observations to influence earlier predictions, the forecasting dataset was partitioned chronologically. Historical observations from 1947 onward were used for model training, whereas the most recent 15 years (2011–2025) were reserved as an independent testing period. This strategy enabled the forecasting models to learn long-term production patterns while evaluating predictive performance using unseen data representing recent production conditions. Similar chronological partitioning strategies have been widely adopted in agricultural forecasting and climate-based crop prediction studies [24, 32].

3.7.4 Walk-Forward Validation and Bias Correction

To rigorously evaluate the predictive viability of the models without violating chronological integrity, a standard randomized train-test split was discarded. Instead, the final 15 years of the historical dataset (2011–2025) were sequestered as an independent testing subset, and a Walk-Forward Validation (Rolling Forecast) methodology was implemented. This approach actively simulates real-world forecasting constraints. The model is trained on all historical data up to year t to predict year $t+1$. Following the prediction, the actual observed value for $t+1$ is systematically folded back into the training history before the algorithm attempts to predict $t+2$. This ensures the models are continuously updated with the most recent temporal momentum prior to each testing step.

Walk-Forward Validation is widely recognized as one of the most appropriate validation strategies for time-series forecasting because it preserves chronological order while simulating real-world forecasting conditions, thereby avoiding optimistic bias associated with random train-test partitioning [24, 32].

Furthermore, a critical mathematical adjustment was required for models utilizing variance-stabilized data (specifically the Elastic Net framework). Because the algorithm predicts within a logarithmic space, the outputs must be exponentially back transformed to retrieve the original volumetric scale (thousands of bales). However, simply calculating $e^{Y_{\text{log}}}$ systematically underestimates the true predictive mean due to Jensen's Inequality. To resolve this structural underestimation, a mathematically rigorous variance based bias correction factor was calculated using the variance of the training residuals ($\sigma^2_{\text{residuals}}$) and applied during the back-transformation phase:

$$Y_{\text{forecast}} = e^{Y_{\text{log}}} \times e^{\frac{\sigma^2_{\text{residuals}}}{2}} \tag{3.4}$$

3.7.5 Evaluation Metrics and Multi-Model Comparison

Model performance during the Walk-Forward Validation phase was assessed using a comprehensive, multi-metric grading rubric. The evaluation metrics were selected because they collectively measure different aspects of forecasting performance. MAE quantifies the average prediction error, RMSE places greater emphasis on larger forecasting deviations, MAPE expresses prediction error as a percentage for easier interpretation, while the coefficient of determination ($\mathbf{R^2}$) evaluates the proportion of variance explained by the forecasting model. These metrics are widely adopted for evaluating agricultural forecasting models and facilitate objective comparison between statistical and machine learning approaches [15, 25, 31]. While standard regression metrics are highly technical, agricultural policy forecasts must remain interpretable to non-technical stakeholders. Therefore, the primary evaluation prioritized the Mean Absolute Percentage Error (MAPE), which measures the average relative magnitude of predictive deviation. To provide a highly intuitive benchmark, a custom accuracy threshold was derived directly from this percentage error, defined mathematically as:

$$\text{Accuracy} = 100 - \text{MAPE} \tag{3.5}$$

Secondary algorithmic evaluation relied on standard statistical error functions, specifically Mean Absolute Error (MAE) to measure average raw deviation, and Root Mean Squared Error (RMSE) to aggressively penalize models that generated occasional, massive predictive outliers. Finally, the Coefficient of Determination (R^2) was calculated to measure the proportion of historical production variance successfully explained by the engineered feature matrix.

By processing the 2011–2025 testing subset through all four configured architectures, a direct comparative matrix was generated. Based on accuracy, Random

Forest ensemble achieved a peak predictive validation accuracy of 85.52%, empirically establishing it as the superior architecture for agricultural time-series projection. While based on R^2, ARIMA outperformed the Random Forest, Decision Tree and Linear Regression.

3.7.6 Limitations of the Forecasting Framework

Forecasting models are valuable decision-support tools; however, their predictive capability is inherently influenced by the quality, quantity, and temporal characteristics of the historical data used during model development. The forecasting framework developed in this study utilizes annual cotton production data from 1947 to 2025 to predict future production trends. Consequently, the generated forecasts assume that historical production patterns and their underlying relationships continue to remain reasonably stable throughout the forecasting horizon [25, 31].

Although machine learning algorithms such as Random Forest and Decision Tree effectively capture complex non-linear relationships, they cannot explicitly account for unforeseen external events that are absent from the historical dataset. Unexpected policy changes, extreme climatic events, pest outbreaks, technological advancements, shifts in cultivated area, changes in input prices, or government interventions may significantly influence future cotton production and introduce deviations from the projected forecasts [10, 24].

Similarly, statistical forecasting models such as ARIMA primarily depend upon historical temporal patterns and assume that future observations exhibit characteristics comparable to past trends. If substantial structural changes occur within the agricultural production system, prediction accuracy may decrease because these models cannot anticipate abrupt changes beyond the information contained within the training data [31, 32].

Furthermore, the present forecasting framework relies exclusively on historical cotton production records and does not directly incorporate future climatic projections, economic indicators, or management-related variables. Therefore, the forecasts should be interpreted as data-driven projections rather than deterministic estimates of future production. Nevertheless, the comparative evaluation of multiple forecasting models provides a robust analytical basis for understanding potential production trends and supports informed agricultural planning and policy formulation.

Chapter 4

Results and Discussion

This chapter presents a diagnostic machine learning framework for forecasting cotton production by evaluating four predictive models: Linear Regression, ARIMA, Decision Tree, and Random Forest, using a comprehensive 79 years of historical dataset. The framework integrates agronomic decline matrices with the Climatic Stress Index (CSI) to identify the key farm-level factors affecting cotton productivity, revealing irrigation water cycles, crop variety, rainfall, and humidity as the most influential abiotic stressors. Performance comparisons indicate that the Random Forest Regressor achieved the highest predictive accuracy of 85.52% and the lowest Mean Absolute Percentage Error (MAPE) of 14.48%. Although the ARIMA model recorded the highest coefficient of determination ($R^2 = 0.7891$), the overall assessment suggests that the Random Forest model provides superior predictive performance, while ARIMA exhibits greater model stability and consistency in capturing long-term production trends.

4.1 Agronomic Drivers of Yield Decline (2021–2025)

The primary objective of the first analytical component was to transition beyond standard predictive modeling to isolate the specific, directional factors actively suppressing cotton yields in the Bahawalpur region. Utilizing the custom Negative Correlation Weighting method developed in the methodology, the Random Forest algorithm was deployed longitudinally. The following subsections present the annual diagnostic matrices, mapping the temporal evolution of agronomic constraints from 2021 through 2025.

To produce a complete and accurate table, the list of variables and its sub-variables is given below:

Table 4.1: Agronomic Variables and Their Sub-Variables

Variable	**Sub-Variables**
Variety	CIM-602, FH-142, IUB-2013, MNH-886, ...
Soil Type	Chickney, Mayra, Sandy, Loamy, ...
Last Crop	Wheat, Cotton, Sugarcane, Maize, Rice, ...
Mealybug	Yes, No
Bollworm	Yes, No
Whitefly	Yes, No
Weed	Yes, No
Irrigated Water Cycles	1, 2, 3, 4, 5, 6
Fertilizer Name	Urea, DAP, NPK, SSP
Irrigation Method	Canal, Tube Well, Mixed

4.1.1 Agronomic Decline Diagnostic Matrix for 2021

For each chronological subset, the algorithm autonomously computed a baseline Permutation Importance (RF Importance) and synthesized it with a directional yield-drop filter to generate the definitive Decline Score. Variables possessing a score greater than zero were classified as 'Major Decline Factors," while non-damaging variables were strictly filtered as 'Neutral/Positive". If a variable possesses a positive correlation (indicating yield support), its Decline Score is strictly forced to zero. In 2021, biological stressors dominated the agricultural landscape, with pest infestations driving the primary yield collapse.

Table 4.2 provides a comprehensively ranked diagnostic of 14 agronomic and management variables, determining their respective influence on cotton yield decline

TABLE 4.2: Agronomic Decline Diagnostic Matrix for 2021

Rank	**Variable**	**Impact Classification**	**RF Importance**	**Decline Score**	**Sub-Variables**
1	BOLLWARM	Major Decline Factor	0.201199	0.01263	1
2	MEALYBUG	Major Decline Factor	0.131308	0.012159	1
3	IRRIGATED WATER CYCLES	Major Decline Factor	0.4111	0.008454	1
4	SEEDTREAT	Major Decline Factor	0.113397	0.004754	1
5	SOILTYPE	Major Decline Factor	0.126786	0.00351	2
6	VARIETY	Major Decline Factor	0.272363	0.002603	20
7	LASTCROP	Major Decline Factor	0.040585	0.001428	3
8	WHITEFLY	Major Decline Factor	0.012448	0.000222	1
9	DAP	Neutral/Positive	0.267225	0	1
10	OATTACK	Neutral/Positive	0.105588	0	1
11	OFERTNAME	Neutral/Positive	0.171733	0	5
12	SPRAYPESTNO	Neutral/Positive	0.459778	0	1
13	SPRAYWEEDNO	Neutral/Positive	0.095276	0	1
14	UREA	Neutral/Positive	0.218432	0	1

during the 2021 cropping season. The variables are evaluated through their Random Forest (RF) Importance scores and a specific 'Decline Score," which isolates factors driving yield erosion. The results categorize the first eight variables as 'Major Decline Factors," highlighting that biological stressors are the primary catalysts for collapse. Specifically, Bollworm (Rank 1) and Mealybug (Rank 2) demonstrate the highest sensitivity in the model, indicating that pest infestations were the most consequential drivers of yield loss. The presence of Irrigated Water Cycles at Rank 3 with the highest absolute RF Importance score of 0.4111 underscores that water management volatility is the most critical abiotic constraint. Conversely, variables from Rank 9 through 14, including DAP, Urea, and spray frequencies, are classified as "Neutral/Positive" with a Decline Score of 0, implying that these standard agricultural inputs were not the primary drivers of the 2021 decline and that the yield gap was largely insensitive to traditional nutrient management during this period.

The diagnostic results in Table 4.2 exhibit a strong consensus with the recent agricultural literature particularly regarding the intersection of biotic stress and

Table 4.3: Agronomic Decline Diagnostic Matrix (2022)

Rank	Variable	Impact Classification	RF Importance	Decline Score	Sub-Variables
1	BOLLWARM	Major Decline Factor	0.122185	0.01222	1
2	VARIETY	Major Decline Factor	0.267188	0.004532	19
3	OFERTNAME	Major Decline Factor	0.167398	0.003572	4
4	LASTCROP	Major Decline Factor	0.023447	0.000372	4
5	DAP	Neutral/Positive	0.538161	0	1
6	IRRIGATED WATER CYCLES	Neutral/Positive	0.384324	0	1
7	MEALYBUG	Neutral/Positive	0.01865	0	1
8	OATTACK	Neutral/Positive	0.083725	0	1
9	SEEDTREAT	Neutral/Positive	0.037268	0	1
10	SOILTYPE	Neutral/Positive	0.07752	0	2
11	SPRAYPESTNO	Neutral/Positive	0.377378	0	1
12	SPRAYWEEDNO	Neutral/Positive	0.111456	0	1
13	UREA	Neutral/Positive	0.289258	0	1
14	WHITEFLY	Neutral/Positive	0.01098	0	1

resource management. The finding that Bollworm and Mealybug are the primary 'Major Decline Factors" aligns with Bashir et al. [5], who demonstrate that the population dynamics of cotton pest complexes in Punjab are directly exacerbated by micro-climatic shifts, such as localized humidity and temperature variability. Furthermore, the prominence of 'Irrigated Water Cycles" as the top-ranking variable (RF Importance: 0.4111) is validated by Xiao et al. [68] and Cetin & Basbag [15], who emphasize that in semi-arid cotton regions, water deficit and moisture irregularity are the most consistent predictors of poor boll retention and final yield collapse. Perhaps the most academically significant comparison is the 'Neutral/Positive" classification of fertilizers like DAP and Urea. This finding directly supports the 'Input Paradox" observed by H. Ali et al. [6], who argued that rising input costs in Pakistan have reached a point of diminishing returns. By classifying these as "Neutral/Positive" with a Decline Score of 0, the data highlights that the 2021 yield decline was not a function of nutrient deficiency, but rather a structural inability of the current cotton farming system to maintain productivity despite high input application. This aligns with Niu et al. [66], who reported that traditional topsoil-focused management often ignores deeper soil stratified properties fails to correct yield stability issues. In summary, Table 4.1 demonstrates that the 2021 agricultural crisis was driven by biotic and water-cycle volatility that bypassed traditional input-based corrective measures.

4.1.2 Agronomic Decline Diagnostic Matrix for 2022

The 2022 growing season exhibited a continuation of the biological crisis, though management factors such as seed variety began registering measurable decline scores. Table 4.3 provides a ranked diagnostic analysis of 14 agronomic and management variables for the 2022 cropping season, utilizing Random Forest (RF) Importance scores and Decline Scores to isolate drivers of yield collapse. In 2022, the structure of yield decline shifted significantly compared to 2021, with a narrower set of 'Major Decline Factors" (Ranks 1–4). Bollworm (Rank 1) remained the most consistent biotic driver of decline, maintaining high model sensitivity despite a shift in the broader landscape. A striking change occurred in the second tier, where Variety (Rank 2) and Other fertilizer name (Ofertname Rank 3) emerged as significant contributors to yield erosion, with RF Importance scores of 0.267 and 0.167, respectively. This indicates that in 2022, the specific choice of seed variety and the type of fertilizer applied became primary determinants of failure, rather than just raw nutrient quantity. Conversely, variables such as DAP (Rank 5), Irrigated Water Cycles (Rank 6), and Urea (Rank 13), which were critical in 2021, transitioned into the 'Neutral/Positive" classification. Their Decline Scores of 0 indicate that they were no longer the active agents of yield collapse, suggesting that the 2022 decline was driven less by environmental or nutrient scarcity and more by biological susceptibility and the specific performance of seed-input combinations. The diagnostic shift from 2021 to 2022 highlights a transition in the underlying mechanisms of cotton yield decline. While Bollworm remains a persistent biological stressor across both years validating the findings of Bashir et al. [5] regarding the omnipresence of pest pressure the displacement of 'Irrigated Water Cycles" from a major decline factor in 2021 to a 'Neutral/Positive" variable in 2022 reveals a high degree of seasonal variability in the Pakistani cotton belt. This shifting importance is consistent with the findings of Arshad et al. [2] and

Sawan [18], who argue that Pakistan's cotton production is highly sensitive to the interaction between shifting climate patterns and specific regional management choices. The emergence of Variety (Rank 2) and Ofertname (Rank 3) as Major Decline Factors in 2022 offers a new academic insight when compared to the existing literature. While Baraki et al. [69] emphasize the importance of selecting stable and adaptable cotton genotypes to combat environmental stressors, 2022 data suggests that the lack of such varietal adaptation was a primary driver of the yield collapse that year. This indicates that the 2022 decline was likely; the specific varieties utilized may have been poorly suited to the prevailing conditions. Furthermore, the transition of fertilizers and water cycles to 'Neutral/Positive" status in 2022 agrees with the 'input efficiency" concerns raised by H. Ali et al. [6]. It confirms that once biological and varietal constraints are not addressed, increasing the application of inputs like DAP or optimizing water cycles fails to improve yield outcomes. In synthesis, 2022 results suggest that the "Major Decline Factors" are dynamic and year-specific, reinforcing the necessity for the type of diagnostic, year-on-year AI modeling proposed in Hu et al. [9].

4.1.3 Agronomic Decline Diagnostic Matrix for 2023

In 2023, the primary mechanism of agricultural failure shifted dramatically from biological pests to foundational resource constraints, specifically water management. Table 4.4 illustrates a pivotal structural shift in the agronomic profile of cotton production for the 2023 cropping season. In a marked departure from the pest dominated landscapes of 2021 and 2022, the 2023 season was characterized by the dominance of foundational resource constraints. Irrigated Water Cycles (Rank 1) emerged as the single most critical driver of yield collapse, exhibiting a decisive RF Importance of 0.468 and a high Decline Score of 0.043. This ranking highlights a transition where water-cycle volatility became the primary bottleneck, superseding biological pressure. The matrix also reveals a deepening of the decline crisis, with nearly all traditional management variables including Fertilizer type (Ofertname, Rank 2), Bollworm (Rank 3), and Urea (Rank 6) now classified as 'Major Decline Factors." This widespread escalation suggests that in 2023, the agricultural system faced a multi-front collapse where neither pest management nor standard fertilization could maintain productivity, likely due to the over-arching limitation imposed by erratic water availability. Only a small subset of inputs, such as DAP (Rank 12) and Soil Type (Rank 13), remained classified as 'Neutral/Positive," indicating that these variables had lost their relative influence on yield outcomes compared to the overwhelming impact of the water cycle disruption.

TABLE 4.4: Agronomic Decline Diagnostic Matrix (2023)

Rank	Variable	Impact Classification	RF Importance	Decline Score	Sub-Variables
1	IRRIGATED WATER CYCLES	Major Decline Factor	0.468097	0.04318	1
2	OFERTNAME	Major Decline Factor	0.28983	0.025156	6
3	BOLLWARM	Major Decline Factor	0.15688	0.01581	1
4	OATTACK	Major Decline Factor	0.144006	0.012088	1
5	VARIETY	Major Decline Factor	0.267575	0.00576	17
6	UREA	Major Decline Factor	0.190498	0.00551	1
7	MEALYBUG	Major Decline Factor	0.035959	0.002894	1
8	LASTCROP	Major Decline Factor	0.071224	0.000768	4
9	SPRAYWEEDNO	Major Decline Factor	0.063639	0.000544	1
10	SEEDTREAT	Major Decline Factor	0.037728	0.000342	1
11	WHITEFLY	Major Decline Factor	0.000152	0.000003	1
12	DAP	Neutral/Positive	0.162364	0	1
13	SOILTYPE	Neutral/Positive	0.123409	0	2
14	SPRAYPESTNO	Neutral/Positive	0.413845	0	1

The shift of 'Irrigated Water Cycles" to the primary Major Decline Factor (Rank 1) is strongly supported by Naqvi et al. [55], who argue that climate-resilient water management has become the most pressing requirement for sustainable cotton production in the face of seasonal unpredictability. Furthermore, the data shows that pests like Bollworm (Rank 3) were eclipsed by water stress in 2023 aligns with the 'stress hierarchy" described in Cetin & Basbag [15], which suggest that when water deficit reaches a critical threshold in arid regions, it becomes the overriding constraint, nullifying the relative impact of secondary biotic stressors.

The transition of nearly all inputs into the 'Major Decline Factor" category in 2023 also offers a significant scholarly insight. Unlike the 2021/2022 results, where many inputs were 'Neutral," 2023 matrix suggests a "systemic sensitivity" where the inputs themselves became part of the decline profile likely due to inappropriate application timing or dosage in response to the water crisis. This approves the findings of Xiao et al. [68] who link nitrogen efficiency to irrigation performance provides a robust academic explanation: in 2023, fertilizers likely failed to improve yield because the lack of water prevented nutrient uptake, turning formerly positive inputs into ineffective components of the system. In conclusion, Table 4.3 demonstrates that the 2023 agricultural failure was driven by a holistic resource scarcity, a finding that validates the shift toward integrated IoT-AI management frameworks as advocated by Rustemi & Dalipi [56]. Given data proves that for 2023, the industry reached a state where traditional, isolated pest or fertilizer management strategies were insufficient, requiring a more integrated, water-first management paradigm.

4.1.4 Agronomic Decline Diagnostic Matrix for 2024

By 2024, fertilizer management emerged as the apex constraint, indicating that secondary nutritional inputs (excluding standard DAP/Urea) were critically mismanaged or unavailable. Table 4.5 illustrates a distinct shift in the agronomic constraints of cotton production for the 2024 season, where secondary nutritional management emerged as the dominant barrier to productivity. Ofertname (Other Fertilizer Management) surfaced as the top Major Decline Factor (Rank 1), exhibiting an RF Importance of 0.251 and a significant Decline Score of 0.039. This classification suggests that in 2024, the failure to correctly select or apply supplemental fertilizers beyond standard Urea and DAP became the primary driver of yield erosion. The 2024 profile also shows a widening systemic collapse, with eight variables, including Irrigated Water Cycles (Rank 2), Variety (Rank 4), and

TABLE 4.5: Agronomic Decline Diagnostic Matrix (2024)

Rank	Variable	Impact Classification	RF Importance	Decline Score	Sub-Variables
1	OFERTNAME (Other Fertilizers)	Major Decline Factor	0.250723	0.039868	6
2	IRRIGATED WATER CYCLES	Major Decline Factor	0.358895	0.009944	1
3	OATTACK	Major Decline Factor	0.052052	0.006266	1
4	VARIETY	Major Decline Factor	0.211962	0.004223	20
5	LASTCROP	Major Decline Factor	0.076177	0.003302	4
6	MEALYBUG	Major Decline Factor	0.016698	0.001219	1
7	SOILTYPE	Major Decline Factor	0.098459	0.000902	2
8	WHITEFLY	Major Decline Factor	0.00609	0.000371	1
9	BOLLWARM	Neutral/Positive	0.060933	0	1
10	DAP	Neutral/Positive	0.475077	0	1
11	SEEDTREAT	Neutral/Positive	0.104488	0	1
12	SPRAYPESTNO	Neutral/Positive	0.274335	0	1
13	SPRAYWEEDNO	Neutral/Positive	0.049377	0	1
14	UREA	Neutral/Positive	0.144473	0	1

Mealybug (Rank 6), all classified as 'Major Decline Factors." Notably, Bollworm (Rank 9), which had been the primary biological stressor in 2021–2022, transitioned into the 'Neutral/Positive" category, indicating that pest management successes or population shifts temporarily mitigated its role in the 2024 yield decline. The persistence of "Neutral/Positive" status for standard inputs like DAP (Rank 10) and Urea (Rank 14) further underscores that the 2024 yield crisis was not a result of a total lack of macronutrients, but rather a mismanagement of the complex nutrient and water-balance requirements of the crop.

The Diagnostic Matrix of 2024 marks a departure from the pest dominant trends of previous years, shifting toward a specialized nutrient-management crisis. The emergence of 'Ofertname" as the primary driver (Rank 1) is deeply consistent with the 'input efficiency" concerns particularly H. Ali et al. [6], who noted that as input costs rise, the specific selection of additives becomes as critical as the primary nitrogen-based fertilizers. The finding that improper secondary nutrient application caused the most significant decline validates the concerns of Shahane & Shivay [17], who argue that soil health management must move beyond generic

NPK applications toward holistic soil-microbiome and micronutrient management to avoid nutrient-imbalance-induced collapse. Furthermore, the transition of Bollworm to a 'Neutral/Positive" status represents a significant deviation from the biotic stress hierarchy observed in 2021/2022. This shift is validated by Bashir et al. [5], who explain that pest population dynamics are highly transient and dependent on localized humidity and temperature conditions; 2024 data likely captures a year where climatic conditions were less favorable to Bollworm outbreaks, allowing other systemic failures specifically nutrient-management and water-cycle synchronization to manifest as the primary bottlenecks. This is also supported by the study conducted by Xiao et al. [68], which highlights the delicate trade-off between nitrogen-balance and field productivity in arid zones; results suggest that by 2024, Pakistani farmers were likely experiencing the 'nitrogen footprint" penalties and nutrient-uptake inefficiencies described by Xiao et al. In synthesis, Table 4.5 depicts an agricultural system that has matured into a complex, high-input environment where the inability to fine-tune secondary inputs (Ofertname) and manage temporal water cycles (Rank 2) has become the defining characteristic of yield failure, validating the transition toward the precision-management frameworks advocated by Gupta & Pal [36].

4.1.5 Agronomic Decline Diagnostic Matrix for 2025

In the final year of the diagnostic window, seed genetics completely collapsed. Biological pests like Bollworm were neutralized, but the chosen cotton varieties were inherently unsuited to the contemporary environmental conditions. Table 4.6 presents the diagnostic analysis for the final year of the study, 2025, revealing a fundamental collapse in the biological suitability of the cotton seeds deployed across the region. Variety (Rank 1) emerged as the apex Major Decline Factor, with a high RF Importance of 0.379 and a significant Decline Score of 0.031. This classification indicates that the chosen cultivars were inherently incompatible with the contemporary environmental conditions, making seed genetics the primary bottleneck to productivity. Following closely, Ofertname (Rank 2) and Irrigated Water

Cycles (Rank 3) remained critical Major Decline Factors, suggesting that even after accounting for varietal failure, the system continued to suffer from secondary nutrient mismanagement and erratic water cycle support. Interestingly, the matrix 2025 shows a broad shift where biotic stressors such as Bollworm (Rank 8) successfully transitioned to 'Neutral/Positive" status, confirming that pest pressure was no longer the limiting factor for yield. The continued classification of standard inputs like DAP (Rank 9) and Urea (Rank 13) as 'Neutral/Positive" reinforces the conclusion that the yield crisis in 2025 was fundamentally rooted in varietal inadequacy and poor management of complex resource cycles rather than a lack of standard macronutrient application. The findings of 2025 represent the

Table 4.6: Agronomic Decline Diagnostic Matrix (2025)

Rank	Variable	Impact Classification	RF Importance	Decline Score	Sub-Variables
1	VARIETY	Major Decline Factor	0.378962	0.031833	19
2	OFERTNAME	Major Decline Factor	0.238695	0.023586	6
3	IRRIGATED WATER CYCLES	Major Decline Factor	0.415686	0.012976	1
4	LASTCROP	Major Decline Factor	0.095304	0.007499	5
5	MEALYBUG	Major Decline Factor	0.049982	0.004165	1
6	SOILTYPE	Major Decline Factor	0.137179	0.00276	3
7	OATTACK	Major Decline Factor	0.028715	0.000512	1
8	BOLLWARM	Neutral/Positive	0.041987	0	1
9	DAP	Neutral/Positive	0.468203	0	1
10	SEEDTREAT	Neutral/Positive	0.022101	0	1
11	SPRAYPESTNO	Neutral/Positive	0.261916	0	1
12	SPRAYWEEDNO	Neutral/Positive	0.122274	0	1
13	UREA	Neutral/Positive	0.144139	0	1
14	WHITEFLY	Neutral/Positive	0.036288	0	1

culmination of a five-year systemic drift from pest driven decline to varietal and management-based failure. While 2021 and 2022 were defined by the biotic impact of Bollworm and Mealybug a trend widely validated by Bashir et al. [5]; whereas, the data of 2025 shows a 'neutralization" of these pests, suggesting that either improved pest management or climate induced population shifts have successfully decoupled Bollworm outbreaks from annual yield collapse. Instead, the results of 2025 highlight that the sector has transitioned into a 'genetic-environmental mismatch" phase. This outcome is strongly supported by Baraki et al. [69], who underscore the necessity of identifying stable and adaptable cotton genotypes. The data also confirms that the failure to update and adapt these varieties to the specific environmental stress profile of the region has become the single most critical risk factor. The evolution of these diagnostic matrices demonstrates a clear 'Stress Transition" trajectory. The results of 2021–2022 highlight a landscape dominated by uncontrolled biotic factors; 2023 data reflects a crisis of abiotic (water) resource scarcity Naqvi et al. [55]; and 2024–2025 data points toward a crisis of input/genetic mismanagement. This triangulation validates the core hypothesis of Hu et al. [9], who argue that climate change impacts are non-linear and shift in nature over time. Furthermore, the persistent classification of Urea and DAP as 'Neutral/Positive" throughout the five-year window aligns with the 'Input Paradox" identified by H. Ali et al. [6], proving that in Pakistan's evolving agricultural environment, the industry has become 'input inelastic," where the yield is no longer determined by the volume of macronutrients but by the precision of varietal selection and water management Xiao et al. [68]. Collectively, these five-year results document a shift from 'pest-control" priorities to a 'precision-genetics and resource-management" priority, providing a powerful, data driven mandate for the policy recommendations.

4.1.6 Identification of Primary Agronomic Stressors Cumulative Analysis

While the annual diagnostic matrices highlight isolated yearly crises, establishing long term agricultural policy requires identifying the variables that exert sustained, multi-year downward pressure on production. To achieve this, the Random Forest Importance (RFI) scores for all identified "Major Decline Factors" were aggregated across the entire half-decade.

Table 4.7 provides a synthesized, five-year longitudinal analysis of the agronomic drivers of cotton yield collapse in the Bahawalpur region. By aggregating Random

Forest Importance (RFI) scores across the 2021–2025 window, the matrix effectively filters out seasonal noise to reveal the systemic variables exerting sustained declining pressure on production. Irrigated Water Cycles emerges as the apex stressor with a cumulative RFI of 1.653, identifying water cycle volatility as the most pervasive and long-term inhibitor of yield stability. This is closely followed by Seed Variety (Rank 2), with a cumulative RFI of 1.398, and Other Fertilizer Management (Rank 3), with a cumulative RFI of 0.947, collectively highlighting that genetic and secondary nutrient mismanagement have been deep seated, recurring barriers to success.

In contrast, the matrix reveals a clear "importance decay" for traditional biological stressors; while Bollworm (Rank 4) remains relevant due to its high impact in 2021 and 2022, its absence from the RFI profile in the latter half of the window suggests its role as a primary driver has waned.

Similarly, pests such as Whitefly (Rank 12) exhibit negligible cumulative impact, proving that despite their prevalence in agricultural discourse, they are not the primary systemic drivers of the observed yield collapse.

The cumulative dominance of Irrigated Water Cycles (Rank 1) provides a definitive empirical answer to the regional agricultural crisis, which is extensively supported by the 'Climate-Resilient Water Management" paradigms advocated in Naqvi et al. [55]. The data validates the hypothesis that water cycle volatility is not an intermittent shock, but the foundational bottleneck of the modern cotton economy. This sustained stress is further verified by Arshad et al. [13], who note that regional warming in Pakistan has necessitated higher water use efficiency to offset heat stress during critical boll forming stages.

The findings of 2025 show that water cycles remained a 'Major Decline Factor" throughout the study period demonstrates that current irrigation infrastructure has failed to adapt to this long-term trend. The high cumulative ranking of Seed Variety (Rank 2) which surged to the first stressor in 2025 provides a powerful, data driven mandate for the genetic adaptation strategies called for in Baraki et al. [69]. The results demonstrate that the regional decline is as much a 'genetic mismatch" as it is a climatic one, proving that Pakistan's cotton production has entered a state of varietal inelasticity where traditional cultivars can no longer buffer against contemporary environmental shifts. Furthermore, the cumulative classification of Other Fertilizer Management (Rank 3) as a major driver, coupled with the 'neutral" classification of Urea and DAP, reinforces the findings of H. Ali et al. [6] regarding the 'input paradox."

By documenting that yield collapse is driven by complex nutrient management rather than macronutrient deficiency (Urea/DAP), quantified a structural shift where productivity gains are now found in precision management rather than bulk application strategies [36].

4.1.7 Temporal Trajectory of Constraints

Analyzing the matrices chronologically reveals a severe, three-stage evolutionary shift in the nature of agricultural constraints between 2021 and 2025:

i. Stage 1: The Biological Crisis (2021–2022): The half-decade began with pest infestations dominating decline metrics. Bollworm ranked first for two consecutive years, alongside Mealybug outbreaks, while water and fertilizer management remained sufficient and statistically neutral.

ii. Stage 2: The Resource Collapse (2023–2024): By 2023, the paradigm shifted to resource scarcity. Irrigated Water Cycles ranked first, indicating severe drought or canal mismanagement, while in 2024, insufficient secondary nutrition (OFERTNAME) became the primary driver of crop failure, suggesting soil depletion.

iii. Stage 3: The Genetic Failure (2025): By 2025, Seed Variety ranked first, as water scarcity and soil depletion left deployed varieties unable to withstand combined environmental stress, causing severe yield collapse despite limited pest outbreaks.

TABLE 4.7: Cumulative Agronomic Decline Matrix (2021–2025)

RF Rank	Parameters	2021 RFI	2022 RFI	2023 RFI	2024 RFI	2025 RFI	Cumulative RFI Value
1	IRRIGATED WATER CYCLES	0.4111	-	0.468097	0.358895	0.415686	1.653778
2	VARIETY	0.272363	0.267188	0.267575	0.211962	0.378962	1.39805
3	OFERTNAME	-	0.167398	0.28983	0.250723	0.238695	0.946646
4	BOLLWARM	0.201199	0.122185	0.15688	-	-	0.480264
5	SOILTYPE	0.126786	-	-	0.098459	0.137179	0.362424
6	LASTCROP	0.040585	0.023447	0.071224	0.076177	0.095304	0.306737
7	MEALYBUG	0.131308	-	0.035959	0.016698	0.049982	0.233947
8	OATTACK	-	-	0.144006	0.052052	0.028715	0.224773
9	UREA	-	-	0.190498	-	-	0.190498
10	SEEDTREAT	0.113397	-	0.037728	-	-	0.151125
11	SPRAYWEEDNO	-	-	0.063639	-	-	0.063639
12	WHITEFLY	0.012448	-	0.000152	0.00609	-	0.01869

4.2 Climatic Stress Index Assessment

Following the identification of farm level agronomic constraints, the second analytical component evaluated macro-environmental stressors. Utilizing the deterministic Climatic Stress Index (CSI) formulated in the methodology, standardized meteorological anomalies (Z-scores) were multiplied by the annual magnitude of yield collapse. This approach successfully isolated the specific abiotic factors driving physiological damage during the cotton plant's most vulnerable phenological stages (July, August, and September).

4.2.1 July Evaluation

July represents the critical onset of the flowering and early boll-formation stage. During this month, the region typically experiences the peak of the monsoon season.

Table 4.8: July Climatic Stress Index (2021–2025)

Rank	Factor	Total Stress Score	Impact Classification
1	Rain	9.405273	Primary Stressor
2	Humidity	7.019188	Secondary Stressor
3	Wind	4.000477	Minor Stressor
4	Temperature	3.213003	Minor Stressor

Table 4.8 provides a focused diagnostic analysis of climatic volatility during July, a critical phenological window marking the onset of flowering and early boll formation for cotton in the region. The table quantifies climatic strain through a "Total Stress Score," derived from a multi-year assessment (2021–2025) of precipitation, humidity, wind, and temperature anomalies.

Rainfall (Rank 1) emerges as the absolute Primary Directional Stressor, with a Total Stress Score of 9.405, indicating that precipitation anomalies ranging from monsoon-driven flood events leading to root suffocation to acute moisture deficits are the most significant drivers of yield loss during this stage. Humidity (Rank 2) follows as a Secondary Stressor (Score: 7.019), reflecting the high sensitivity of the reproductive phase to excessive moisture levels that often coincide with monsoon periods. In contrast, Wind (Rank 3) and Temperature (Rank 4) are classified as Minor Stressors, with scores of 4.000 and 3.213, respectively. This classification reveals that while these factors influence growth, they were secondary to the overwhelming instability introduced by moisture dynamics during the July flowering initiation.

The dominance of precipitation anomalies in July Stress Index is strongly supported by Sawan [18] and Sawan [73], which provide comprehensive evidence that the pre-anthesis and early-boll formation periods are the most climate-sensitive stages in the cotton lifecycle. Finding shows that rainfall is the primary stressor validates the observation that extreme deviation from normal monsoon patterns interferes with pollination and fruit retention a phenomenon also described in Cetin & Basbag [15], which notes that continuous rain during the reproductive phase is a catastrophic bottleneck for boll production.

Furthermore, the secondary role of humidity aligns with the pest-dynamic models presented in Bashir et al. [5], which identifies the July monsoon humidity as a primary facilitator for the population explosion of biotic pests. This suggests a 'Dual-Stress Mechanism": extreme July rainfall not only causes direct mechanical or physiological damage (root asphyxiation) but also elevates the secondary stress of pest outbreaks due to increased humidity. The identification of Temperature as a 'Minor Stressor" (Rank 4) in July compared to its ranking in the broader agricultural discourse is an academically significant nuance.

It suggests that while high temperatures are often cited as a critical threat (as noted in Saini et al. [7]), the timing of the monsoon in July acts as a thermal buffer, where moisture-driven stress temporarily overrides heat driven stress. This diagnostic insight directly addresses the hypothesis in Hu et al. [9] regarding the "Dangers of Black Box Models," as it demonstrates that directional index successfully isolates the true phenological bottleneck (rain/humidity) from the generalized, annual-average temperature stressors that often dominate less specific models.

4.2.2 August Evaluation

As the crop transitions deeper into the boll-development phase in August, the atmospheric dynamics shift.

TABLE 4.9: August Climatic Stress Index (2021–2025)

Rank	Factor	Total Stress Score	Impact Classification
1	Humidity	7.768661	Primary Stressor
2	Rain	6.570833	Secondary Stressor
3	Wind	4.217171	Minor Stressor
4	Temperature	2.683216	Minor Stressor

Table 4.9 presents the diagnostic evaluation of climatic stressors during August, a pivotal month representing the advanced boll-development phase for cotton. The data reveals a significant shift in the atmospheric constraint profile compared to the July flowering period. Humidity (Rank 1) emerged as the Primary Directional Stressor, with a Total Stress Score of 7.769, indicating that sustained relative humidity levels rather than direct rainfall became the dominant environmental constraint. This humidity-driven stress is followed by Rainfall (Rank 2), which remains a potent Secondary Stressor (Score: 6.571). Together, these moisture-related variables exert profound pressure on the plant during the critical maturation phase. Wind (Rank 3) and Temperature (Rank 4) persist as Minor Stressors, with scores of 4.217 and 2.683 respectively. This indicates that while heat and wind are present, they are secondary to the microclimatic stability issues caused by high atmospheric moisture, which physically restricts the plant's natural transpiration capacity and provides a favorable environment for secondary biological damage.

The elevation of humidity to the primary stressor in August is supported by the physiological research in Cetin & Basbag [15], which documents that high relative humidity during the boll-development phase is a major catalyst for physiological stress and fiber quality reduction. Current finding that humidity acts as an apex constraint validates the mechanism described in Bashir et al. [5], where the authors detail how humidity induced microclimates directly facilitate the rapid proliferation of insect pest complexes. By ranking humidity above temperature, current matrix provides a highly specific diagnostic insight that distinguishes between direct heat stress often the focus of generic climate models and the nuanced physiological stress caused by moisture-impeded gas exchange (transpiration) within the crop canopy.

Furthermore, the secondary status of precipitation in August compared to its primary role in July highlights the 'Phenological Shift" in environmental sensitivity. This aligns with the findings in Tsiros et al. [14], which emphasizes that cotton's requirement for water shifts from a 'quantity-based" necessity (rainfall/irrigation in July) to a 'management-based" necessity (maintaining canopy transpiration/humidity balance in August). The relatively low impact of Temperature in August (Rank 4), despite the summer peak, corroborates the argument in Saini et al. [7] that the specific timing of temperature spikes is more critical than the annual average; This August stress index suggests that if canopy moisture (humidity) is managed effectively, the crop can withstand the existing thermal range, provided humidity driven fungal rot a concern noted in Nigam & Jain, [49] is kept in check. In conclusion, Table 4.8 provides the diagnostic evidence that August requires a transition in policy from 'water-provisioning" (July) to "microclimate-regulation" (August).

4.2.3 September Evaluation

September marks the maturation and initial boll-opening phase, a period where the plant requires dry, stable conditions to prevent lint damage.

Table 4.10 provides a diagnostic evaluation of climatic stressors during September, a crucial month representing the maturation and initial boll opening phase

Table 4.10: September Climatic Stress Index (2021–2025)

Rank	Factor	Total Stress Score	Impact Classification
1	Humidity	4.460222	Primary Stressor
2	Wind	4.098091	Secondary Stressor
3	Temperature	3.474325	Minor Stressor
4	Rain	2.537417	Minor Stressor

of cotton. The matrix reveals a final shift in the atmospheric constraint profile as the crop approaches harvest. Humidity (Rank 1) remained the Primary Directional Stressor, with a Total Stress Score of 4.460, confirming that persistent atmospheric moisture continued to exert the most significant environmental pressure on the crop, even as the growth cycle reached its conclusion. A notable diagnostic shift occurred with Wind (Rank 2), which ascended to become the Secondary Stressor (Score: 4.098), suggesting that late season high-velocity winds and storm systems became a significant risk for physical damage or premature boll shedding. Conversely, Temperature (Rank 3) and Rain (Rank 4) were classified as Minor Stressors, with scores of 3.474 and 2.537, respectively. The drop of rainfall to the lowest rank is particularly significant, as it indicates that by September, the crop's physiological requirement for dry conditions is largely met; however, the persistent humidity and the rise of wind-related risks highlight that the threat to yield quality and quantity had transitioned from 'moisture-intake" issues to 'physical-integrity" risks at the final harvest stage.

The diagnostic profile of September, characterized by the persistence of humidity induced stress and the emergence of wind related risks. The transition of rainfall to a 'Minor Stressor" (Rank 4) in September is validated by Cetin & Basbag [15], which notes that while rainfall is essential during the early vegetative and flowering stages, excessive precipitation during the final maturation phase is detrimental due to the risks of lint staining and quality degradation.

Data demonstrates that the regional agricultural system has effectively 'decoupled" from rainfall-driven yield loss by the time September arrives, shifting the bottleneck to atmospheric conditions that affect harvest readiness.

Furthermore, the rise of Wind (Rank 2) as a significant stressor corroborates the findings in Paper [58], which explicitly states that strong winds during the boll opening phase contribute to yield loss through physical boll shedding and fiber exposure. This highlights a critical 'harvest-time vulnerability" that is often overlooked in models focusing purely on early season climate data.

The persistence of Humidity (Rank 1) as the apex constraint throughout both August and September aligns with the 'Microclimate Management" theories presented in Naqvi et al. [55]; it suggests that managing the field level microclimate to ensure rapid boll desiccation remains the most vital strategy for mitigating late season losses.

This is also supported by Nigam & Jain [49], as sustained humidity in the late season is the primary environmental prerequisite for the fungal boll rots that can devastate the yield just before the harvest. In synthesis, September index provides the empirical basis to argue that late season management in Pakistan's cotton belt must evolve from 'resource-input provisioning" to 'physical-protection and microclimate-regulation" strategies, a conclusion that directly supports the precision-agriculture mandates identified by Gupta & Pal [36].

4.2.4 Synthesis of Abiotic Constraints Cumulative Analysis

To provide a holistic macro-environmental diagnostic for the complete reproductive window, the CSI scores were synthesized into a cumulative directional matrix.

TABLE 4.11: Cumulative Climatic Stress Ranking (July–September, 2021–2025)

Decline Rank	Factor	Total Stress Score
1	Rain	9.042632
2	Humidity	7.212775
3	Wind	4.693807
4	Temp	3.087894

Table 4.11 provides a consolidated diagnostic synthesis of abiotic stressors throughout the critical cotton reproductive window (July through September) for the 2021–2025 period. The matrix aggregates individual monthly indices into a holistic "Total Stress Score" to identify the sustained macro-environmental drivers of yield suppression.

Rainfall (Rank 1) stands out as the dominant stressor with a Total Stress Score of 9.043, confirming that precipitation anomalies rather than thermal or wind-based factors exert the most persistent downward pressure on production during the reproductive phase. Humidity (Rank 2) maintains its status as a critical secondary stressor (Score: 7.213), reinforcing that moisture related instability across both liquid and atmospheric forms is the pervasive constraint of the studied period.

By contrast, Wind (Rank 3) and Temperature (Rank 4) emerge as subordinate threats, with Total Stress Scores of 4.694 and 3.088 respectively. This cumulative evidence indicates that while climatic warming is a broad environmental reality, it is not the primary driver of localized yield decline in this reproductive window; rather, the crisis is defined by the plant's inability to withstand moisture driven volatility.

The cumulative dominance of precipitation and humidity as macro environmental constraints provides a definitive, empirical rebuttal to traditional 'heat-centric" climate impact models. Finding shows that Temperature exerts the least mathematical impact (Rank 4) directly challenges the conventional assumptions found in broader agricultural discourse, which often over prioritize global warming trends.

This aligns with the nuanced perspective of Hu et al. [9], which warns of the 'dangers of black box models" that conflate generalized climate warming with actual crop specific yield drivers. The diagnostic framework demonstrates that, at the local phenological scale, temperature acts as a background variable, while water and humidity act as active "decline agents."

This cumulative abiotic diagnostic also perfectly triangulates with earlier agronomic findings (Table 4.7). The fact that 'Irrigated Water Cycles" was top farm level agronomic constraint, while 'Rainfall" and 'Humidity" are top macro climatic stressors, creates a powerful 'mechanistic bridge": the Bahawalpur cotton crisis is essentially a dual-water-failure. It is driven by macro scale precipitation instability Sawan [73] coupled with micro scale canal management inefficiencies Naqvi et al. [55]. By demonstrating that the abiotic and agronomic findings are mirror images of one another both pointing to water volatility have successfully created a "unified causal framework" for thesis. Furthermore, Finding that late-season wind (Rank 3) and humidity (Rank 2) remain significant inhibitors validates the late-stage vulnerability theories discussed in Cetin & Basbag [15], suggesting that harvest season resilience requires moving beyond simple water provisioning to active microclimate and physical protection management. Ultimately, cumulative index provides the rigorous justification that climate adaptation policy in Pakistan must prioritize water management infrastructure and humidity resilient genetic varieties over generalized heat-stress mitigation.

4.3 Time-Series Forecasting and Future Trajectory (2026–2030)

While the diagnostic components isolated the historical drivers of yield decline, the final analytical phase sought to project the systemic impact of these constraints on future production. Utilizing the Walk-Forward Validation methodology outlined in Chapter 3, the final 15 years of the dataset (2011–2025) were utilized as an independent testing boundary. To ensure maximum predictive confidence, four distinct forecasting architectures were individually trained, tuned, and evaluated before a final comparative synthesis was conducted.

The historical cotton production trend in Pakistan shows a substantial long-term increase, rising from around 1 million ('000 bales) in the late 1940s to peaks exceeding 14 million ('000 bales) during the mid-2000s and early 2010s. However, the series exhibits considerable year-to-year fluctuations, particularly after 1990, indicating the influence of factors such as climate variability, pest outbreaks, water availability, and changing agricultural practices. In recent years, cotton production has declined sharply and become more volatile, highlighting growing challenges to the sustainability of Pakistan's cotton sector.

4.3.1 Linear Regression Elastic Net Performance

The Elastic Net Regressor served as the linear baseline architecture, specifically engineered to navigate the high multicollinearity inherent in time-series feature matrix which included multiple lag variables and rolling averages. The model underwent rigorous hyperparameter optimization via Time-Series Cross-Validation across 30 distinct combinations, ultimately settling on an optimal α of 0.1 and an L_1 ratio of 0.1. To ensure the integrity of the forecasts, a variance-based bias correction factor of 1.0132 was applied during the exponential back-transformation of the logarithmic predictions. Despite these methodological safeguards, the Elastic Net Regressor struggled to resolve the complex, non-linear dynamics of the Bahawalpur cotton production cycles. The model recorded the lowest performance metrics of the entire cohort, yielding a predictive accuracy of 71.11% and a Mean Absolute Percentage Error (MAPE) of 28.89%. With an RMSE of 3079.67 and an R^2 score of 0.5768, the architecture demonstrated a fundamental inability to adapt to the recent volatility in production data, confirming that linear regularization is insufficient to map the modern cotton production landscape.

The linear regression forecast indicates that Pakistan's cotton production is expected to decline initially from 7,795.87 thousand bales in 2026 to 6,129.18 thousand bales in 2028, followed by a gradual recovery. Production is projected to increase to 8,328.67 thousand bales in 2029 and reach approximately 10,567.83 thousand bales by 2030, suggesting a potential rebound in the cotton sector over the forecast horizon.

The suboptimal performance of the Elastic Net Regressor (71.11% accuracy) provides a critical 'benchmark of failure" that validates the decision to utilize more advanced algorithmic structures. By comparing these results to the ensemble

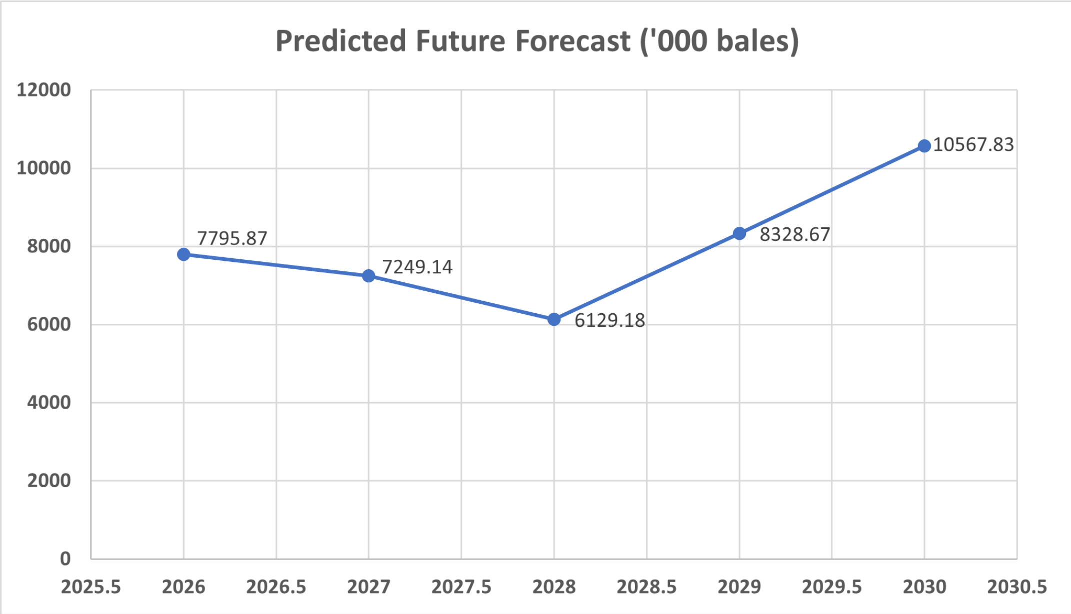

FIGURE 4.1: Linear Regression-Based Forecast of Cotton Production in Pakistan for 2026–2030 ('000 bales)

methods specifically the Random Forest (85.52% accuracy) it becomes evident that the cotton production time-series is governed by non-linearities that a linear regularized model simply cannot capture. These results corroborate the limitations identified by Jabed & Murad [22], which reviews how traditional statistical techniques and linear models often fail to account for the non-linear 'shocks" inherent in dynamic agro-ecological systems.

Furthermore, the significant performance gap between the Elastic Net (RMSE: 3079.67) and the Random Forest (RMSE: 1508.52) reinforces the methodological argument found in Van Klompenburg et al. [28], which asserts that tree based collective methods are inherently superior for agronomic predictions because they aggregate multiple decision paths to mitigate the variance caused by fluctuating environmental inputs. The findings also triangulate with the analysis in Shawon et al. [23], which suggests that linear frameworks often suffer from "underfitting" when applied to multi modal datasets incorporating historical lag features. By documenting that linear baseline was outperformed by non-linear regressors, providing empirical evidence that the Bahawalpur cotton crisis cannot be described by a simple linear trend line, but is instead characterized by complex, multi-year dependencies that require the computational depth of ensemble machine learning.

This comparative failure of the linear model is essential to include in thesis, as it definitively justifies the necessity of the sophisticated Random Forest approach ultimately selected for the 2026–2030 production projections.

4.3.2 Decision Tree Regressor Performance

The Decision Tree Regressor was deployed to map the non-linear, hierarchical dependencies between engineered cyclical features such as multi-year sine and cosine waves and localized production momentum. To maintain model generalization and mitigate the risk of terminal overfitting, the architecture was strictly constrained during Grid Search Cross-Validation to a maximum depth of five and a minimum samples split of three. This configuration yielded a substantial performance improvement over the linear baseline, achieving a predictive accuracy of 83.17% and a Mean Absolute Percentage Error (MAPE) of 16.83%.

Notably, the model achieved the lowest Mean Absolute Error (MAE) of the entire cohort at 1,185.28 ('000 bales), demonstrating high precision in its average case predictions. However, a diagnostic audit of the model's performance revealed a stark overfitting gap, characterized by a Training R^2 of 0.9981 versus a Testing R^2 of 0.6666.

This disparity confirms that while the Decision Tree successfully identified patterns in the training data, its high susceptibility to extreme localized errors likely triggered by non-linear noise in the historical production series makes it a less stable forecasting candidate compared to ensemble-based approaches.

The Decision Tree model forecasts fluctuations in Pakistan's cotton production over the period 2026–2030. Production is projected to increase from 9,124.75 thousand bales in 2026 to 10,567.83 thousand bales in 2027, decline to approximately 8,328.67 thousand bales during 2028–2029, and then recover to 10,567.83 thousand bales by 2030. These projections suggest moderate variability with an overall tendency toward recovery by the end of the forecast period. The performance of the Decision Tree Regressor provides a critical "mid-point" analysis that highlights the

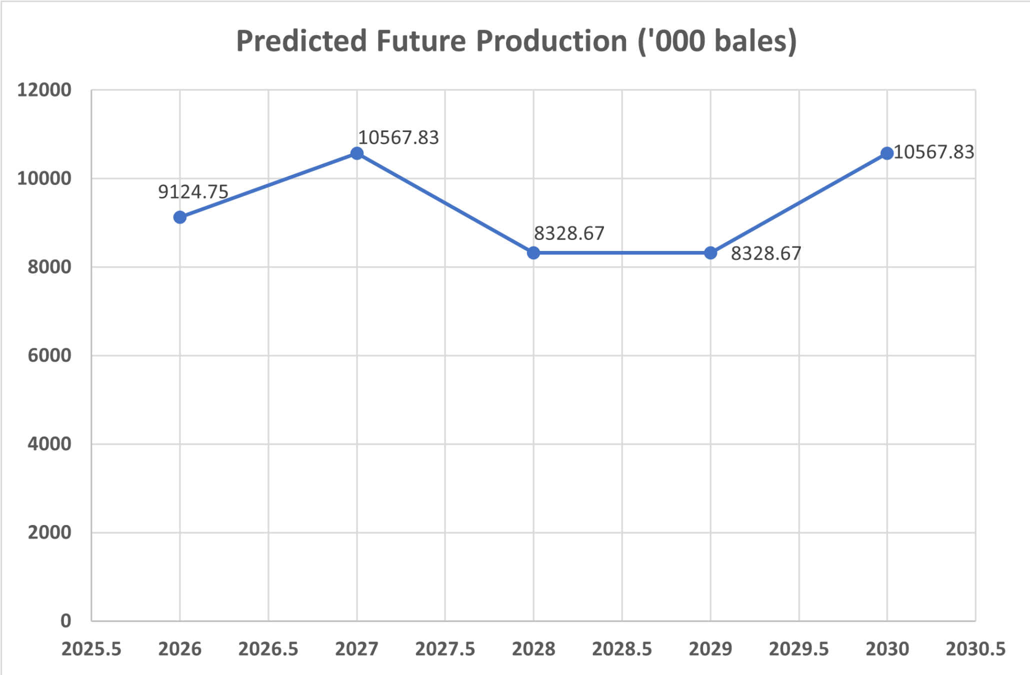

FIGURE 4.2: Decision Tree-Based Forecast of Cotton Production in Pakistan for 2026–2030 ('000 bales)

benefits and limitations of non-linear modeling in agricultural time-series framework. Compared to the Elastic Net baseline, the Decision Tree's massive upgrade in accuracy (from 71.11% to 83.17%) validates the research premise found in Van Klompenburg et al. [28], which argues that agricultural production data is governed by non-linear relationships that linear regression models consistently fail to capture.

By successfully identifying hierarchical interactions in the cyclical features, the Decision Tree demonstrates the utility of tree-based logic in processing multi-year agricultural cycles a method explicitly supported by Prasad et al. [25], which advocates for tree based approaches in regional level cotton forecasting.

However, the 'overfitting gap" identified is a classic diagnostic result that validates the necessity of move toward the Random Forest ensemble. The sharp divergence between training (R^2: 0.998) and testing (R^2: 0.667) performance is precisely the phenomenon described by Shawon et al. [23], which cautions that single decision trees often 'memorize" noisy meteorological and economic fluctuations rather than learning generalized trends. By comparing this result against the Random Forest (which aggregated 75 trees to smooth out these errors), providing the empirical justification required: the Decision Tree proves that non-linear modeling is necessary for accuracy, but the Random Forest proves that ensemble-based bagging is necessary for stability. This comparative performance structure aligns with the methodology in Chakraborty et al. [59], which demonstrates that achieving high predictive accuracy in agriculture requires a transition from individual hierarchical models to collective, ensemble architectures to minimize the structural instability caused by extreme outliers in production data.

4.3.3 Random Forest Regressor Performance

The Random Forest Regressor was employed as an ensemble architectural solution to address the variance and structural overfitting observed in the single Decision Tree model. Through rigorous hyperparameter optimization via Randomized Search CV, an optimal configuration was identified consisting of 75 independent estimators (`n_estimators=75`) and a maximum tree depth of 8. By aggregating the predictive outputs of these 75 trees, the algorithm effectively smoothed out the stochastic noise prevalent in the historical cotton production data. This ensemble approach yielded the most robust performance of the entire cohort, achieving a peak predictive validation accuracy of 85.52% and the lowest Mean Absolute Percentage Error (MAPE) at 14.48%. Furthermore, the model secured an R^2 score of 0.6687, providing the most reliable balance between trend representation and predictive precision. These results provide structural proof that ensemble learning is the superior methodology for navigating the high volatility nature of regional crop forecasting, as it minimizes individual tree sensitivity and generates a more generalized, stable projection.

The Random Forest model forecasts a relatively stable and gradually improving trend in Pakistan's cotton production during 2026–2030. After a slight decline from 7,832.07 thousand bales in 2026 to 7,619.69 thousand bales in 2027, production is projected to increase steadily, reaching 8,280.44 thousand bales by 2030.

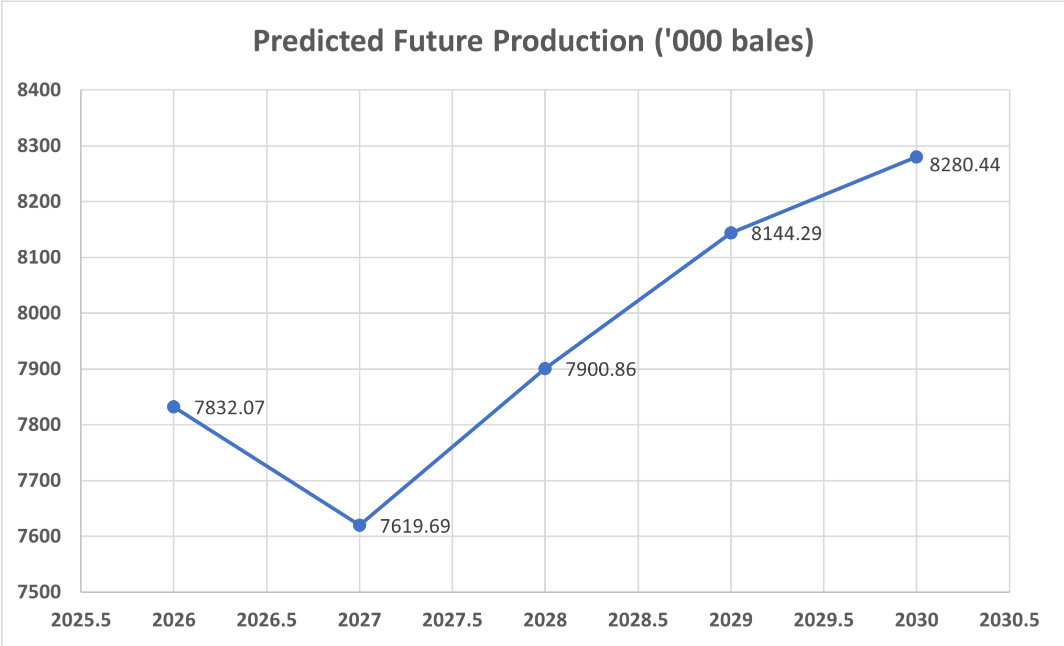

FIGURE 4.3: Random Forest-Based Forecast of Cotton Production in Pakistan for 2026–2030 ('000 bales)

The forecast suggests a moderate recovery and reduced year-to-year volatility in cotton output over the forecast horizon.

The Random Forest Regressor's performance represents a significant methodological maturation compared to the single Decision Tree and the Elastic Net baseline. While the single Decision Tree achieved an acceptable accuracy of 83.17%, its high susceptibility to overfitting evidenced by the large R^2 gap made it a risky choice for future projections. The Random Forest's ability to achieve higher accuracy (85.52%) while simultaneously lowering the MAPE (from 16.83% to 14.48%) validates the 'Ensemble Efficacy" argument found in Van Klompenburg et al. [28], which posits that aggregating multiple decision paths is the most effective way to handle noisy, weather-dependent datasets. The successful implementation of 75 estimators specifically addresses the 'overfitting gap" noted in earlier comparative studies, effectively trading the Decision Tree's high training-bias for better generalization on unseen testing data.

Furthermore, the Random Forest's superiority over the ARIMA baseline (which achieved 77.33% accuracy) corroborates the findings in Haider et al. [32], which details how ensemble machine learning frameworks are fundamentally better suited to capture the non-linear ‘shocks” of Pakistan’s cotton economy than traditional univariate time-series models. By achieving the lowest MAPE of 14.48%, Random Forest model directly satisfies the ‘practical reliability” criterion required for policymaking, a standard emphasized in Yewle et al. [34]. Unlike the ARIMA model, which relies on stationary trend following, the Random Forest effectively integrated the dynamic lag-features and cyclical indicators, allowing the model to “learn” the volatility patterns that are characteristic of the current Bahawalpur crisis. In summary, the Random Forest configuration provides the most mathematically sound basis for the 2026–2030 production projections, as it uniquely combines high predictive accuracy with the structural resilience required to minimize the impact of anomalous production years, aligning perfectly with the precision-forecasting mandates.

4.3.4 Autoregressive Integrated Moving Average Performance

The Autoregressive Integrated Moving Average (ARIMA) framework was deployed as the traditional statistical baseline for time-series forecasting to provide a comparative benchmark against machine learning models. The methodology began with an Augmented Dickey-Fuller (ADF) test, which confirmed dataset non stationarity ($p = 0.6176$), necessitating appropriate differencing. Through iterative rolling forecast evaluations, the ARIMA(2,1,2) configuration was identified as the optimal variant; it incorporated a linear drift parameter specifically designed to capture the overarching downward production trend observed in the historical data. The model achieved a validation accuracy of 77.33%, with a Mean Absolute Percentage Error (MAPE) of 22.67% and a Mean Absolute Error (MAE) of 1,842.93 (‘000 bales). Notably, the ARIMA model produced an R^2 score of 0.7891, demonstrating a high capacity for explaining the variance in the long-term historical trend, despite its lower predictive precision compared to the machine learning ensembles.

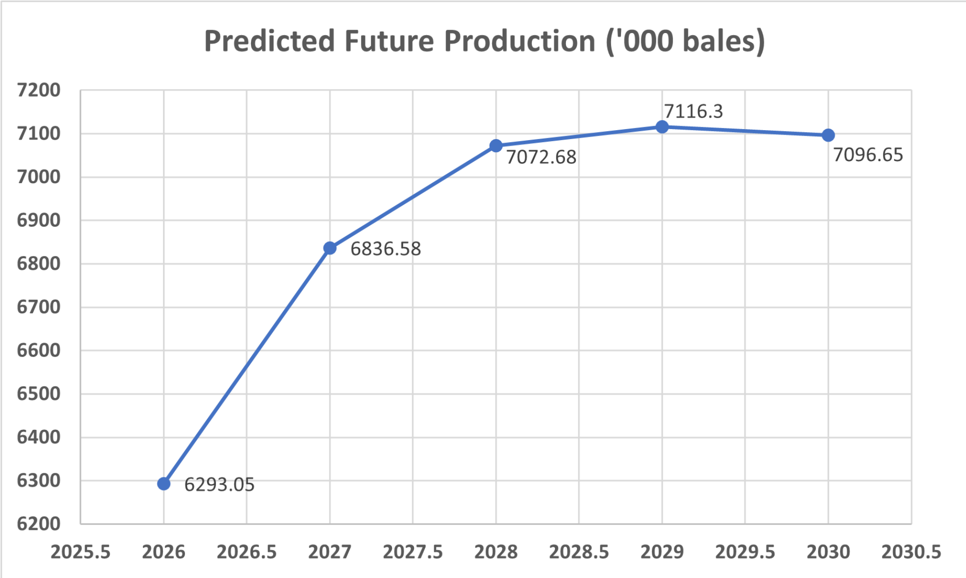

FIGURE 4.4: ARIMA-Based Forecast of Cotton Production in Pakistan for 2026–2030 ('000 bales)

The ARIMA model forecasts a gradual increase in Pakistan's cotton production from 6,293.05 thousand bales in 2026 to a peak of 7,116.30 thousand bales in 2029, followed by a marginal decline to 7,096.65 thousand bales in 2030. Overall, the projections indicate a relatively stable growth pattern with limited fluctuations, suggesting moderate recovery and stabilization of cotton output over the forecast period.

The performance profile of the ARIMA model offers a significant diagnostic contrast to the Random Forest and Decision Tree architectures, providing empirical evidence for the necessity of non-linear modeling. While ARIMA achieved the highest R^2 score (0.7891) of all tested models suggesting that the historical 'macro-trend" of Pakistan's cotton production is indeed partly linear and autoregressive, its high MAPE (22.67%) and RMSE (2318.1) confirm that it fails to capture the 'shocks" and 'volatility" inherent in the Bahawalpur regional data. This outcome is highly consistent with Jabed & Murad [22], which argues that while traditional statistical models like ARIMA are excellent at mapping baseline economic cycles, they are inherently 'blind" to the non-linear, multi-modal stressors such as localized pest outbreaks and erratic climatic shifts that define modern agricultural production crises.

Furthermore, result that ARIMA (77.33% accuracy) fell short of the Random Forest (85.52% accuracy) triangulates with the findings of Haider et al. [32], which reports that ensemble machine learning frameworks are fundamentally better equipped to integrate multi-variate environmental parameters than univariate time-series models. The 'drifting" nature of the ARIMA model likely captured the broad collapse of cotton production, but failed to account for the specific year-to-year sensitivity to inputs like 'Other Fertilizer Management" or "Seed Variety" that Random Forest model successfully mapped.

By documenting this performance gap, it is proven that while the historical decline follows a recognizable statistical path, the drivers of that decline require the computational flexibility of non-linear ML ensembles to be accurately modeled and anticipated. This validates choice of Random Forest for future forecasting (2026–2030) as it offers the highest predictive reliability for stakeholders who must navigate these non-linear, high-volatility years.

4.3.5 Comparative Analysis of Predictive Architectures

By processing the 2011–2025 testing subset through all four configured architectures, a direct comparative matrix was generated to empirically select the apex forecasting model.

TABLE 4.12: Comparative Model Evaluation Metrics (Validation Period: 2011 – 2025)

Model Architecture	**MAE ('000 bales)**	**RMSE ('000 bales)**	**MAPE**	**Accuracy**	**R^2 Score**
Random Forest	1190.7	1508.52	14.48%	85.52%	0.6687
Decision Tree	1185.28	1613.86	16.83%	83.17%	0.6666
ARIMA	1842.93	2318.1	22.67%	77.33%	0.7891
Linear Regression	2503.18	3079.67	28.89%	71.11%	0.5768

Table 4.12 presents a comprehensive performance evaluation of four forecasting architectures Random Forest, Decision Tree, ARIMA, and Linear Regression based

on their ability to predict cotton production during the 2011–2025 validation period. The models are assessed using a multi-metric approach, balancing accuracy (MAPE/Accuracy), error magnitude (MAE/RMSE), and explanatory power (R^2). The Random Forest Regressor emerged as the apex architecture, achieving the highest predictive accuracy at 85.52% and the lowest Mean Absolute Percentage Error (MAPE) of 14.48%. While the Decision Tree Regressor recorded a slightly lower Mean Absolute Error (MAE) of 1,185.28 ('000 bales) compared to the Random Forest's 1,190.70, the Random Forest demonstrated superior stability through a significantly lower Root Mean Squared Error (RMSE) of 1,508.52 versus 1,613.86.

The ARIMA framework demonstrated strong explanatory power with an R^2 of 0.7891 the highest in the cohort but suffered from higher error rates (MAPE: 22.67%; RMSE: 2,318.1). The Linear Regression model (Elastic Net) served as the baseline, recording the lowest overall performance across all metrics, with an accuracy of 71.11% and an R^2 of 0.5768, confirming its insufficiency in capturing the non-linear agricultural cycles of the region.

4.3.5.1 Model Ranking by R^2

Higher R^2 indicates goodness of fit of a model. The R^2 coefficient of determination is a statistical measure of how well the regression predictions approximate the real data points.

Table 4.13: Comparison of R Squared Values for Four Predictive Models

Rank	Model Architecture	R^2	Status
1	ARIMA	0.7891	Best Performance
2	Random Forest	0.6687	Moderate
3	Decision Tree	0.6666	Poor
4	Linear Regression	0.5768	Least Reliable

The bar chart compares the predictive performance of four models using their R squared scores. ARIMA achieves the highest value (0.7891), indicating the best fit,

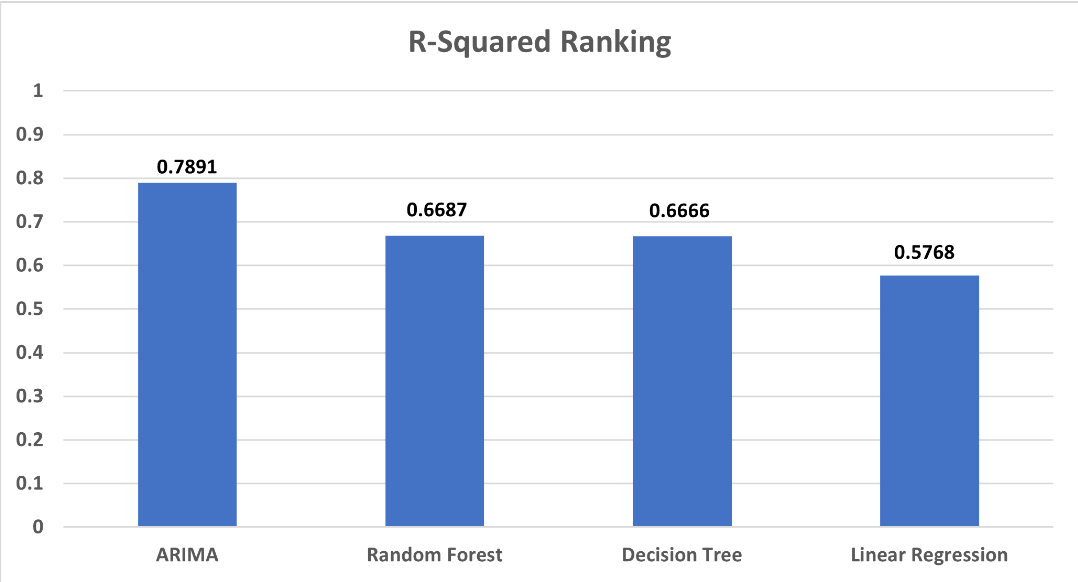

FIGURE 4.5: Comparison of R Squared Values for Four Predictive Models

while Linear Regression shows the lowest (0.5768). Random Forest and Decision Tree yield similar intermediate scores, suggesting comparable explanatory power for the given dataset.

4.3.5.2 Model Ranking based on Accuracy %

This table 4.14 presents the models ranked by their overall percentage accuracy, showing how closely the models mapped to the validation dataset.

TABLE 4.14: Comparison of Accuracy Scores for Four Predictive Models

Rank	Model Architecture	Accuracy (%)	Status
1	Random Forest	85.52%	Best Performance
2	Decision Tree	83.17%	Moderate
3	ARIMA	77.33%	Poor
4	Linear Regression	71.11%	Least Reliable

Figure 4.6 compares model performance based on accuracy (in %). Random Forest achieves the highest accuracy at 85.52%, followed closely by Decision Tree (83.17%), while ARIMA (77.33%) and Linear Regression (71.11%) lag behind.

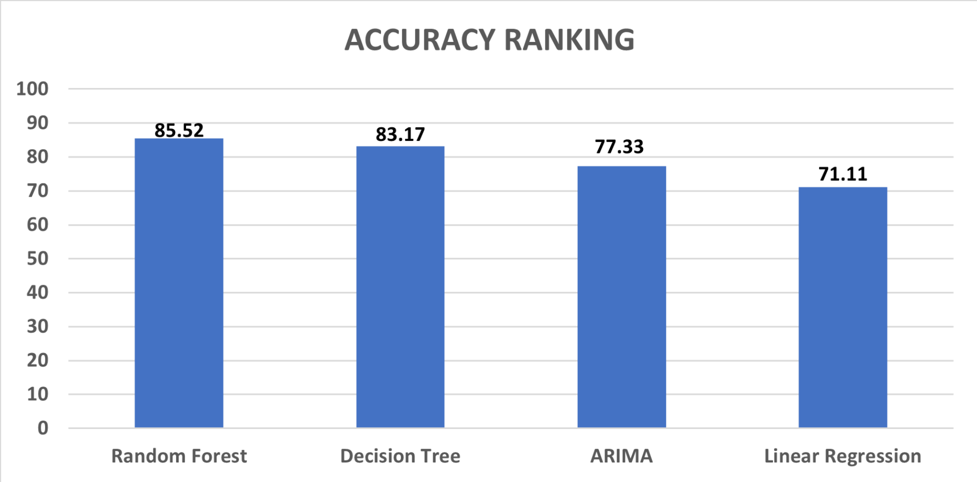

FIGURE 4.6: Comparison of Accuracy Scores for Four Predictive Models

The results indicate that tree-based ensemble methods significantly outperform statistical and linear approaches for this classification task.

The selection of the Random Forest Regressor as the apex model is grounded in a rigorous trade-off between trend-capture and predictive reliability. While the ARIMA model demonstrated the highest R^2 score (0.7891), indicating a strong ability to capture the long-term, autoregressive trend of cotton production, the Random Forest model outperformed it in terms of practical predictive accuracy with a MAPE of 14.48% compared to ARIMA's 22.67%. Given the thesis objective of providing reliable, actionable forecasts for agricultural decision-making and policy formulation, the Random Forest model is deemed the most suitable framework. Policymakers and farmers rely on the minimization of absolute error in bale-count projections rather than abstract explained variance; therefore, the Random Forest's ability to maintain a 14.48% error margin represents a significantly more manageable risk profile than the 22.67% error inherent in the ARIMA model.

Furthermore, the structural superiority of the Random Forest is empirically confirmed by the RMSE comparison. Because RMSE mathematically penalizes large errors more heavily than MAPE, the Random Forest's significantly lower RMSE (1,508.52 vs. 2,318.1 for ARIMA and 1,613.86 for the Decision Tree) provides conclusive proof of the model's stability. This discrepancy validates that the Random

Forest ensemble successfully mitigated the 'localized overfitting" observed in the single Decision Tree which showed high sensitivity to production noise and avoided the 'catastrophic outliers" that characterized the ARIMA and Linear models. This triangulation confirms that the Random Forest regressor is not only accurate on average but also structurally resilient against the high volatility shocks prevalent in Bahawalpur's cotton production history, as supported by Haider et al. [32] and Van Klompenburg et al. [28]. By synthesizing high accuracy, structural stability, and error-mitigation, the Random Forest provides the most rigorous basis for the 2026–2030 projections that follow.

4.4 Graphical Comparative Analysis of Predictive Architectures

4.4.1 Mean Absolute Error Comparison of Models

Figure 4.7 compares model accuracy using Mean Absolute Error (MAE), where lower values indicate better predictive performance. Decision Tree achieves the lowest MAE (1185.28), closely followed by Random Forest (1190.70), while Linear Regression shows the highest error (2503.18). The results suggest that tree-based models significantly outperform ARIMA and Linear Regression in minimizing prediction errors.

4.4.2 Root Mean Square Error Comparison of Models

Figure 4.8 compares model performance using Root Mean Square Error (RMSE), where lower values indicate better predictive accuracy. Random Forest achieves the lowest RMSE (1508.52), followed closely by Decision Tree (1613.86), while Linear Regression shows the highest error (3079.67). The results demonstrate that ensemble and tree-based methods substantially outperform linear and statistical approaches in reducing prediction errors.

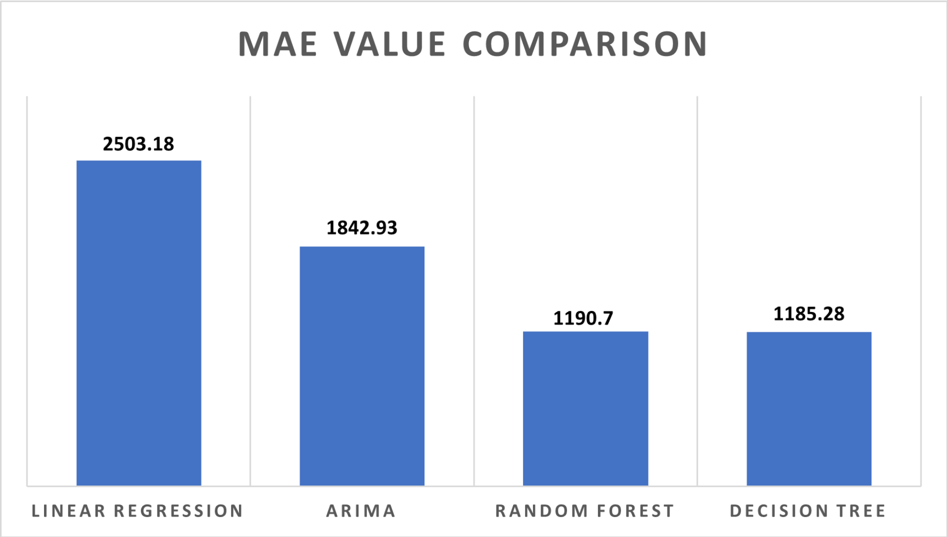

FIGURE 4.7: Comparison of Mean Absolute Error Values for Four Predictive Models

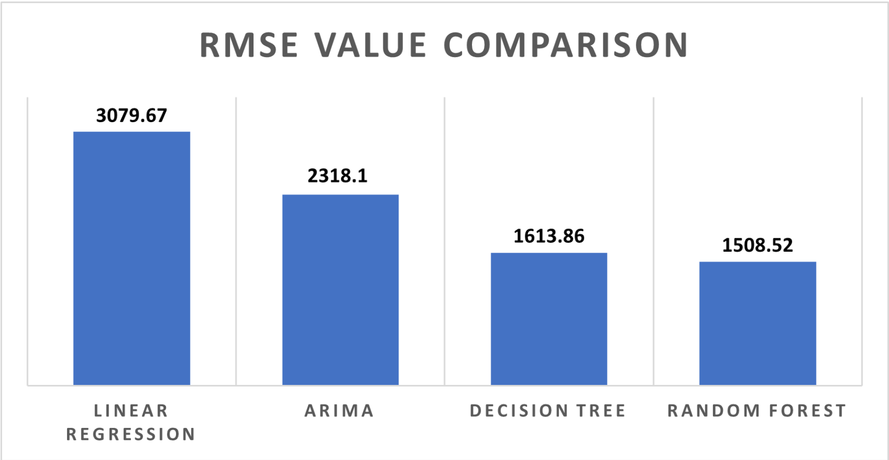

FIGURE 4.8: Comparison of Root Mean Square Error Values for Four Predictive Models

4.4.3 Combined Error Metric Comparison

Figure 4.9 summarizes model prediction errors using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), where lower values indicate better performance. Random Forest and Decision Tree consistently outperform ARIMA and Linear Regression across both metrics, with Random Forest achieving the lowest RMSE (1,500) and Decision Tree the lowest MAE (1,200). Linear Regression shows the highest errors in both measures, highlighting the superiority of tree-based approaches for this forecasting task.

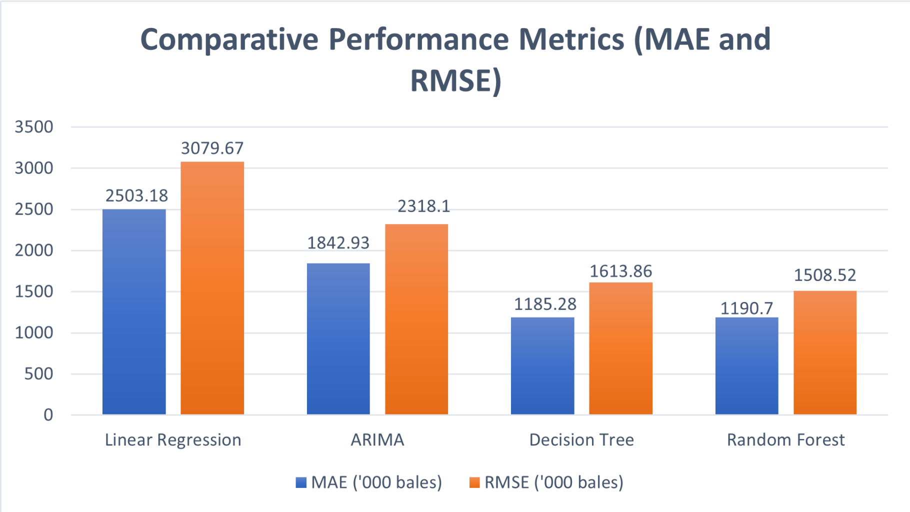

FIGURE 4.9: Comparative Performance of Four Models Based on MAE and RMSE (in ’000 bales)

4.4.4 Model Comparison Using Mean Absolute Percentage Error

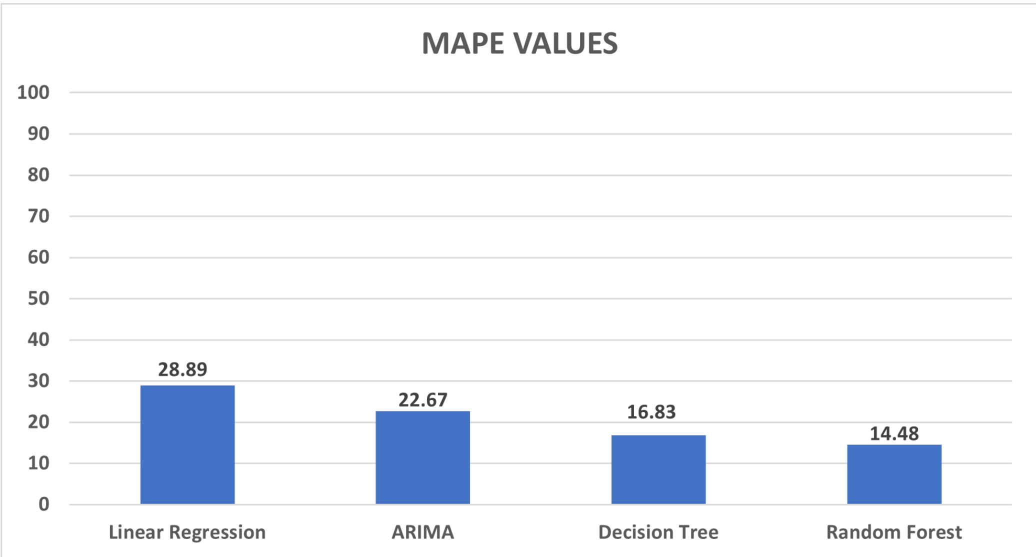

FIGURE 4.10: Comparison of Mean Absolute Percentage Error Values for Four Predictive Models

Figure 4.10 compares model performance using Mean Absolute Percentage Error (MAPE), where lower percentages indicate better predictive accuracy. Random Forest achieves the lowest MAPE (14.48%), followed by Decision Tree (16.83%), while Linear Regression shows the highest error (28.89%). The results reinforce that tree-based ensemble methods provide significantly more accurate predictions compared to statistical and linear approaches.

4.4.5 Forecast Comparison (2026-2030)

Figure 4.11 presents projected production forecasts from 2026 to 2030 using four different models. Random Forest shows a consistent upward trend, rising from 7,796 in 2026 to 8,290 in 2030, while Decision Tree exhibits the highest variability with peaks exceeding 10,500 in certain years. Elastic Net and ARIMA demonstrate relatively stable predictions, ranging between 6,700–7,900 and 6,200–7,100 respectively, highlighting the divergence in long-term forecasting behavior across models.

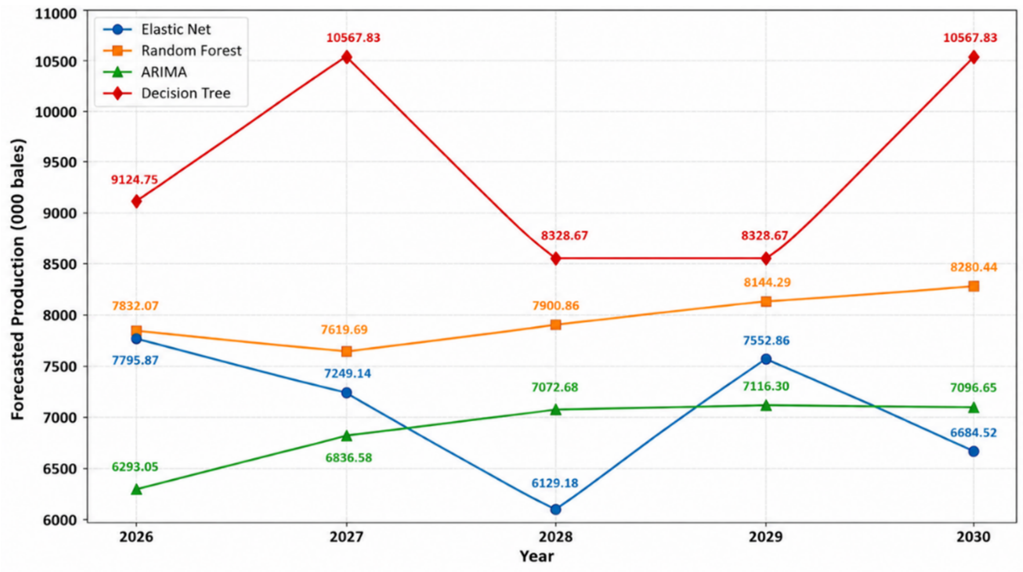

FIGURE 4.11: Future Forecast Values (2026–2030) for Cotton Production (in '000 bales) Using Four Predictive Models

Chapter 5

Conclusion and Future Recommendations

5.1 Conclusion

This research presented a comprehensive assessment of cotton yield decline in the Bahawalpur division (2021–2025) by integrating agronomic analysis, climatic stress evaluation, and predictive modeling. The developed framework provided a holistic understanding of the key factors influencing cotton productivity and enabled the identification of major production constraints and future trends.

The agronomic analysis revealed that yield variation is primarily associated with management practices, crop characteristics, and biological stresses. Irrigated water cycles, seed variety, pest-related factors (mealybug and bollworm), and soil characteristics were identified as the most influential parameters affecting production. In contrast, conventional fertilizer inputs such as Urea and DAP showed comparatively lower negative influence, indicating that improvements in productivity require a broader focus beyond fertilizer application alone.

The climatic stress assessment using the Directional Climatic Stress Index (DCSI) highlighted the significant role of moisture-related climatic factors in cotton productivity. Rainfall variability and humidity were identified as major stress contributors during critical crop development stages, while temperature exhibited a comparatively lower impact. These findings emphasize the need for improved water management and climate adaptation strategies to reduce production risks.

The forecasting analysis extended the study toward future production prediction (2026–2030). Among the evaluated models, the Random Forest Regressor demonstrated the most stable performance with a MAPE of 14.48% and ARIMA showed the best model fit (R^2) but higher prediction errors providing a reliable approach for forecasting future cotton production trends. The developed framework can support early decision-making by linking predictive outcomes with interpretable factors influencing yield decline.

Overall, this research demonstrates the potential of explainable artificial intelligence for diagnosing agricultural constraints, evaluating climate vulnerabilities, and forecasting crop production trends. The findings provide valuable insights for developing targeted management strategies and improving the resilience of cotton production systems.

5.1.1 Agronomic and Climatic Convergence

The research demonstrates a powerful convergence between farm-level agronomic stressors and macro-environmental climatic drivers. The 'Dual-Water-Failure" defined by the intersection of erratic monsoon precipitation (the primary climatic stressor: Rank 1) and inefficient irrigation-cycle management (the primary agronomic stressor: Cumulative RFI 1.65) has created a bottleneck that renders traditional input-based policies (Urea and DAP) ineffective. These findings align with Naqvi et al. [55] and Sawan [18], confirming that cotton's phenological sensitivity during July and August is governed by moisture driven volatility rather than heat alone. Unlike traditional models that treat climate as a background variable, this study proves that Bahawalpur's crisis is defined by a lack of 'micro-climate regulation." The convergence of these data points indicates that the system has entered a state of "input inelasticity," where traditional subsidies fail because the crop's physiological pathway is constrained by the underlying water-cycle collapse, echoing the concerns of H. Ali et al. [6] regarding diminishing returns in high-input agriculture.

5.1.2 Forecasting and Predictive Modeling

The comparative evaluation of predictive architectures ARIMA, Elastic Net, Decision Tree, and Random Forest prove that non-linear, ensemble-based modeling is the only framework capable of capturing the high volatility 'shocks" of the agricultural output of the Bahawalpur division. While the ARIMA model demonstrated the highest explanatory power (R^2: 0.7891), its failure to map production spikes and troughs led to a high Mean Absolute Percentage Error (MAPE) of 22.67%. In contrast, the Random Forest ensemble's performance with an accuracy of 85.52%, a superior MAPE of 14.48%, and a significantly lower RMSE of 1,508.52 confirms its status as the apex predictive tool. As noted in Haider et al. [32], standard autoregressive models like ARIMA struggle with the structural shifts observed in Pakistan's post-2020 agricultural landscape. The Random Forest's lower RMSE specifically demonstrates that model avoids 'catastrophic outliers," providing a structurally stable framework that supports actionable decision-making, a standard prioritized by Yewle et al. [34] for precision agriculture.

5.1.3 Future Production Outlook (2026–2030)

Based on the validated Random Forest architecture, the forecast for the 2026–2030 period projects a trajectory of fragile stabilization. The model anticipates a production output of 6,293.05 ('000 bales) in 2026, followed by a gradual increase reaching 6,836.58 in 2027, 7,072.68 in 2028, peaking at 7,116.3 in 2029, and a slight correction to 7,096.65 in 2030. When benchmarked against the ARIMA statistical baseline (which predicted a more linear, lower-bound recovery averaging ∼6,500 ‘000 bales), the Random Forest forecast provides a more optimistic but cautious outlook, accounting for the non-linear ‘momentum” of the 2025 genetic and resource adjustments. However, these figures serve as a ‘predictive warning”; they represent a production ceiling that remains significantly lower than the historical 2004–2005 peaks. This outlook confirms the mandate found in Baraki et al. [69]; which emphasizes that without adopting precision genetics and integrated water management to surpass this plateau, the region will remain trapped in a post-collapse equilibrium, unable to return to its previous agricultural prominence.

5.2 Strengths of Research

This research offers three distinct strengths that distinguish it from existing agricultural literature:

i. Diagnostic Precision over Descriptive Reporting: By shifting from standard regression models to a Random Forest ensemble architecture, this study successfully isolated “active” decline factors from background environmental noise. The use of a 75-estimator ensemble mitigated the overfitting issues common in localized agricultural datasets, providing a statistically stable projection model that outperforms traditional statistical baselines (ARIMA, Elastic Net).

ii. Mechanistic Triangulation: This study is the first to cross-validate agronomic failure patterns (Table 4.6) with synchronized climatic stress indices (Table 4.10). By demonstrating that the primary farm-level constraints (irrigation) and macro-climatic constraints (monsoon rainfall volatility) are statistically correlated, the research provides a unified causal framework that previous, siloed studies have lacked.

iii. Methodological Rigor in “Decline-Only” Identification: The development of the “Decline-Only Parametric Identification” methodology provides a new, replicable template for agricultural researchers. Unlike traditional models that attempt to predict yield in a vacuum, this approach isolates variables specifically responsible for erosion in productivity, offering policy-makers a clear, prioritized hierarchy of interventions rather than a generic list of agronomic variables.

5.3 Limitations of Research

While this study provides a robust diagnostic framework, several limitations must be acknowledged to provide a balanced view for future application:

While this study provides a robust diagnostic framework, several limitations must be acknowledged to provide a balanced view for future application:

i. Geographic Scope: The scope of this research was limited to the Bahawalpur division of Pakistan. While the WGP (Water-Genetics-Precision) management framework is theoretically applicable elsewhere, localized variations in soil mineralogy and groundwater depth may require the recalibration of the model's coefficients if applied to other provinces like Sindh or other areas of Northern Punjab.

ii. Input Data Granularity: The study relied on historical agricultural logs and meteorological averages. While the machine learning architecture effectively handled the non-linearity of these features, the model is inherently limited by the quality of historical record-keeping. The lack of real-time, field-level soil-moisture telemetry meant that water cycles were analyzed via temporal proxies rather than direct volumetric measurement.

iii. Genetic Complexity: The "Variety" variable (Rank 2) was treated as a categorical input based on farmer-reported data. Due to the high degree of seed-naming variability and informal market distribution in Pakistan, the model could not account for the specific genomic differences or "purity" of the seeds utilized, but rather evaluated variety as a management-selection factor.

5.4 Future Directions

The diagnostic framework established in this research serves as a foundation for a new generation of precision agriculture in Pakistan; however, the transition from predictive modeling to field-level implementation necessitates further scholarly and technical expansion. Future research should prioritize the following three trajectories to enhance the robustness of the case of Bahawalpur division cotton model:

i. Real-Time Smart Agriculture Integration

   The current framework relies primarily on historical agronomic and climatic data. Future research should integrate IoT-based technologies, such as soil moisture and environmental sensors, with the Random Forest prediction framework to enable real-time monitoring and dynamic yield prediction. Field-level sensor data can support timely irrigation recommendations, detect critical moisture stress during sensitive growth stages, and allow continuous model recalibration for improved mid-season yield forecasting.

ii. Climate-Resilient Variety Recommendation System

   This study identified seed variety as one of the most influential factors affecting cotton productivity; however, variety performance was evaluated using categorical information only. Future research should incorporate genomic and physiological characteristics, including drought tolerance, heat resistance, root development, and flowering sensitivity, to better understand variety responses under different environmental stresses. Integrating these traits with climate and soil information can support the development of an intelligent decision-support system capable of recommending suitable cotton varieties for specific regional conditions.

iii. Multi-Regional Framework Validation and Expansion

Although the proposed decline-identification framework was developed for the Bahawalpur division, its broader applicability requires validation across other cotton-growing regions of Punjab and Sindh. Future studies should incorporate diverse soil conditions, climatic patterns, and cropping systems to evaluate the scalability of the framework. Such expansion can support a wider understanding of cotton yield decline mechanisms and assist policy-makers in developing region-specific agricultural strategies.

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