ISSN: 2583-7354

International Journal of Emerging Knowledge Studies

Publisher's Home Page: https://www.ijeks.com/

Fully Open Access

Research Paper

Synergistic Impacts of Drought, Salinity, and Temperature on Wheat Productivity

G Praburam[1*] A Srinivasan[2] I Deepika[3] Dr. Aravind Balakrishnan[4]

[1]Assistant Professor, Department of Computer Science and Engineering, Viswam Engineering College, Annamayya District, Andhra Pradesh - 517325, India.
[2]Assistant Professor, Department of Computer Science and Engineering, Viswam Engineering College, Annamayya District, Andhra Pradesh - 517325, India.
[3]Assistant Professor, Department of Computer Science and Engineering, Viswam Engineering College, Annamayya District, Andhra Pradesh - 517325, India.
[4]Associate Professor, Department of Information Technology, Nehru Institute of Engineering and Technology, Coimbatore, Tamil Nadu, 641105, India.
DOI: https://doi.org/10.70333/ijeks-05-04-021
*Corresponding Author: praburam.it@gmail.com

Article Info:- **Received** : 08 March 2026 **Accepted** : 25 March 2026 **Published** : 30 April 2026

Abstract

Abiotic stress responses in wheat are pivotal determinants of grain productivity and long term sustainability in the face of climate variability and land use intensification. Drought, soil salinity, extreme temperatures, and nutrient deficient environments interact to disrupt root water uptake, leaf gas exchange, nutrient assimilation, and reproductive development, ultimately reducing yield potential and grain quality. Unlike single stress experiments, natural field conditions often expose wheat to multiple, simultaneous stresses whose combined effects are frequently non additive and more detrimental than individual stresses alone. Recent advances in physiology, genomics, and systems biology have begun to elucidate the molecular networks governing stress perception, signal transduction, osmotic adjustment, antioxidant defence, and hormonal regulation in wheat. High throughput phenotyping and omics technologies enable the identification of stable yield associated traits and stress tolerant ideotypes suitable for diverse agroecology. This article synthesizes current perspectives on abiotic stress responses in wheat, emphasizing integrative approaches that link genotypic resilience with improved agronomic practices. By highlighting scalable breeding strategies, precision management tools, and resource efficient production systems, the work aims to support sustainable wheat cultivation that maintains productivity while mitigating environmental degradation under increasingly variable climatic conditions.

Keywords: *Drought salinity temperature stress, Physiological stress responses, Osmotic adjustment, Ion homeostasis, Antioxidant defence system, Molecular level adaptation.*

1. Introduction

Wheat is one of the most widely cultivated cereal crops in the world, serving as a primary source of calories and protein for over a third of the global population. Its productivity underpins food security, rural livelihoods, and national food-self-sufficiency strategies, especially in developing regions [1]. However, wheat production is increasingly constrained by abiotic stresses such as drought, heat, salinity, and nutrient-poor soils, all of which are expected to intensify with climate change. These stresses interact in complex, non-additive ways that alter physiological processes, limit yield potential, and threaten long-term agricultural sustainability. Understanding how wheat perceives, transduces, and acclimates to such stresses is therefore essential for developing resilient varieties and management practices. This article explores abiotic stress responses in wheat from a productivity-oriented and sustainability-focused lens, integrating insights from physiology, genetics, breeding, and agronomy to guide future research and policy [2].

1.1 Global significance of wheat and abiotic stress challenges

Wheat accounts for a substantial share of global cereal production and human dietary intake, with billions of people relying on wheat-based staples such as bread, roti, and pasta. The crop is cultivated across diverse agroecology, ranging from high-input temperate systems to rainfed and marginal environments in arid and semi-arid regions [3]. In many of these areas, wheat productivity is already near ecological limits, and further yield gains are increasingly constrained by recurring abiotic stresses rather than by biotic factors such as pests and diseases. Climate-driven changes such as prolonged dry spells, elevated temperatures, erratic rainfall, and secondary soil salinization are exacerbating existing stress regimes and exposing new wheat-growing zones to unfavourable conditions.

Abiotic stress challenges are particularly acute in low- and middle-income countries, where smallholder farmers often lack access to advanced irrigation, precision inputs, or stress-tolerant varieties. Under these conditions, even modest reductions in wheat yield can have disproportionate impacts on household food security, income, and regional stability [4]. Moreover, many wheat-producing regions face trade-offs between intensification for higher productivity and the preservation of soil health, water resources, and biodiversity. In this context, addressing abiotic stress in wheat is not only a biological and agronomic challenge but also a socio-economic and environmental imperative.

1.2 Need for integrated stress-response perspectives

Traditional research on wheat abiotic stress has often focused on single stress factors, such as drought alone or heat alone, under controlled or simplified field conditions. While these studies have yielded valuable insights into stress-specific signalling pathways, adaptive mechanisms, and tolerance traits, they offer only a partial picture of real-world scenarios, where multiple stresses routinely co-occur [5]. Field-level interactions among drought, salinity, heat, and nutrient deficiencies can lead to synergistic or antagonistic effects that are not predictable from single-stress experiments. For example, combined drought and heat may reduce stomatal conductance and photosynthesis more severely than either stress alone, while salinity and nutrient imbalance can jointly impair root growth and ion homeostasis.

An integrated stress-response perspective is therefore essential to understand how wheat genotypes perceive, integrate, and prioritize signals arising from multiple stress sources. Such a perspective requires combining physiological measurements with genomics, transcriptomics, metabolomics, and modelling to identify shared regulatory hubs, stress-specific responses, and trade-offs between growth and stress tolerance [6]. From a breeding and management standpoint, integrated perspectives help in selecting multi-stress-resilient ideotypes, designing robust agronomic interventions, and developing decision-support tools that account for spatial and temporal variability in stress exposure. By adopting a systems-level view of abiotic stress in wheat, researchers and policymakers can better align productivity goals with long-term sustainability and climate resilience.

2. Physiological and Biochemical Responses to Major Abiotic Stresses

Abiotic stresses such as drought, salinity, and temperature extremes induce profound physiological and biochemical changes in wheat, altering water relations, membrane integrity, metabolic fluxes, and redox balance. These responses are initiated at the cellular level and propagate through tissues and organs, ultimately determining growth trajectory and yield potential [7]. Under stress, wheat shifts resources from growth and reproductive processes toward survival mechanisms, including stomatal regulation, osmotic adjustment, antioxidant detoxification, and accumulation of compatible solutes. Understanding these stress-specific and overlapping responses is essential for identifying traits that can be targeted to improve wheat productivity while maintaining metabolic efficiency and stress resilience [8].

2.1 Drought-induced water-use and photosynthetic limitations

Drought stress in wheat disrupts whole-plant water balance by reducing soil moisture availability and increasing vapor-pressure deficit in the atmosphere. As soil water potential declines, root water uptake slows, leading to decreased xylem sap flow and leaf relative water content [9]. Stomatal closure is triggered to limit transpiration water loss, but this also restricts CO_2 diffusion into the leaf, thereby constraining photosynthetic rate and Rubisco activity. Under prolonged drought, photosynthetic capacity declines further due to reduction in chlorophyll content, damage to the photosystem-II reaction centres, and increased photoinhibition under high irradiance [10].

Metabolically, wheat responds by accumulating osmolytes such as proline, sugars, and glycine betaine, which help maintain cell turgor, stabilize proteins, and protect membranes from dehydration-induced damage. At the same time, oxidative stress intensifies as reactive oxygen species (ROS) accumulate due to imbalanced electron transport in the chloroplasts [11]. Enzymatic antioxidants such as superoxide dismutase, catalase, and ascorbate peroxidase are upregulated to scavenge ROS and prevent macromolecular damage. These physiological and biochemical adjustments improve short-term survival but often come at the cost of reduced leaf area expansion, slower canopy development, and ultimately lower grain yield.

2.2 Salt stress and ionic/osmotic imbalance in wheat

Salt stress imposes dual challenges on wheat, osmotic stress due to reduced soil water potential and ionic stress caused by toxic accumulation of Na^+ and Cl^- in tissues [12]. Upon exposure to saline soils, wheat experiences an immediate osmotic shock that limits root water uptake and reduces turgor-driven cell expansion, leading to stunted growth and slower emergence. As Na^+ and Cl^- ions enter the root system and move toward the shoots, they can reach toxic concentrations in sensitive leaf tissues, interfering with essential cation homeostasis and enzyme function.

To mitigate ionic stress, wheat employs several mechanisms, including selective uptake and transport of ions, compartmentalization of Na^+ into vacuoles, and activation of ion-efflux transporters to prevent cytoplasmic overload. K^+ homeostasis is particularly critical because Na^+ can compete with K^+ for binding sites and transport channels, disrupting membrane potentials and enzyme-linked processes [13]. Biochemically, salinity-stressed wheat accumulates compatible solutes such as proline and soluble sugars to maintain osmotic balance, while simultaneously upregulating antioxidant enzymes and stress-responsive proteins to counter oxidative damage. These adaptive responses can partially sustain growth under moderate salinity but often fail under severe or prolonged exposure, resulting in leaf necrosis, reduced tillering, and significant yield penalties [14].

2.3 Temperature-driven impacts on growth and reproduction

Temperature extremes both heat and cold profoundly affect wheat growth and reproductive development, altering phenology, canopy structure, and grain-filling duration. Heat stress during the vegetative phase accelerates leaf appearance and senescence, shortening the effective growth period and reducing photosynthetic canopy area [15]. At the reproductive stage, elevated temperatures can disrupt meiosis, pollen viability, and fertilization, leading to spikelet sterility, reduced grain number per spike, and smaller seed size. In contrast, cold stress during early growth or reproductive phases can slow metabolic rates, increase membrane rigidity, and induce frost-induced tissue damage.

Physiologically, temperature extremes disturb membrane fluidity, protein folding, and enzymatic activity, triggering stress-response pathways that consume energy otherwise allocated to growth. Heat-stressed wheat often exhibits increased transpiration and respiratory rates, which can deplete carbohydrate reserves and impair grain filling [16]. Biochemically, temperature stress induces the expression of heat-shock proteins (HSPs) and cold-inducible (COR) proteins that protect cellular machinery, while also activating antioxidant systems to manage ROS accumulation. These protective mechanisms help sustain short-term survival but may reduce overall biomass and grain yield, particularly when high-temperature episodes coincide with sensitive reproductive windows [17].

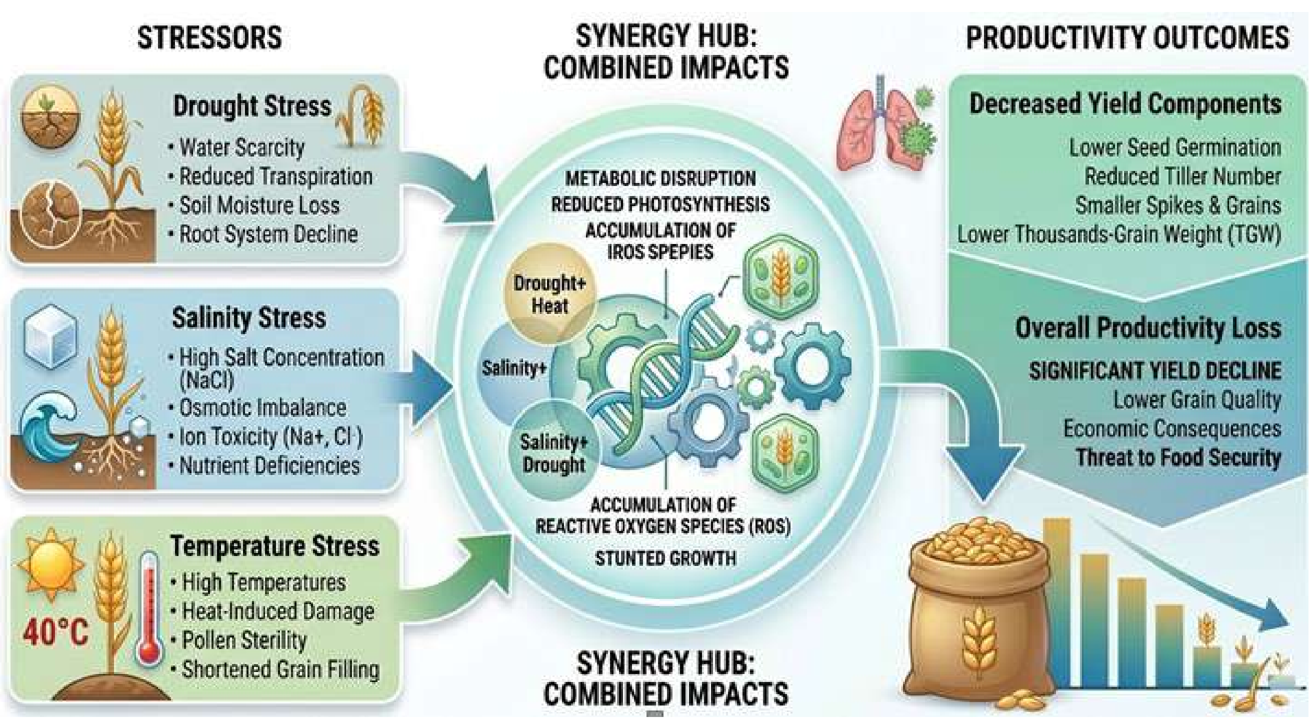

Figure 1. Synergetic impacts of drought, salinity, and temperature on wheat productivity

ISSN: 2583-7354

3. Molecular and Genetic Basis of Stress Tolerance

Understanding the molecular and genetic architecture underlying stress tolerance in wheat is essential to translate physiological observations into heritable, yield-relevant traits [18]. Modern genomics has revealed that abiotic stress responses are orchestrated by complex gene networks, transcription-factor modules, and regulatory RNAs that integrate environmental cues with developmental programs. Natural genetic variation across wheat germplasm further provides a rich reservoir of quantitative trait loci (QTLs) and allelic combinations associated with improved resilience under drought, salinity, and temperature extremes. Together, these layers of regulation enable the identification of superior alleles and molecular markers that can be leveraged in breeding for productivity and sustainability [19].

3.1 Stress-responsive gene networks and signalling pathways

Wheat cells perceive abiotic stresses through membrane-associated sensors and second-messenger systems that initiate intracellular signalling cascades involving calcium, phosphoinositide's, reactive oxygen species, and protein kinases. These signals converge on stress-responsive gene networks that regulate osmolyte biosynthesis, antioxidant enzymes, chaperones, and transporters [20]. A useful way to capture the core-network strength of stress response is through a gene-network centrality index G_{cent}

$$G_{\text{cent}} = \frac{1}{N}\sum_{i=1}^{N}(\deg(v_i)) \qquad (1)$$

where N is the number of co-expressed stress-responsive genes in a network, and $\deg(v_i)$ denotes the number of regulatory interactions (edges) of gene node v_i. Higher G_{cent} indicates a more interconnected, coordinated response, reflecting a robust, polygenic basis of stress tolerance in wheat [21].

3.2 Role of transcription factors and regulatory RNAs

Transcription factors (TFs) act as central hubs in stress-responsive networks by binding to promoter regions of target genes and modulating their expression. Families such as DREB, NAC, MYB, and bZIP are particularly important in drought, salinity, and temperature responses in wheat. Regulatory RNAs including microRNAs (miRNAs) and long non-coding RNAs (lncRNAs) fine-tune TF activity and mRNA stability in a tissue- and stress-specific manner [22]. A composite regulatory-control index R_{ctrl} can express the relative contribution of TFs and regulatory RNAs to stress signalling

$$R_{\text{ctrl}} = \omega_{\text{TF}} \cdot T_{\text{TF}} + \omega_{\text{RNA}} \cdot R_{\text{RNA}} \qquad (2)$$

where T_{TF} is the fraction of differentially expressed TFs among stress-responsive genes, R_{RNA} is the proportion of stress-regulated non-coding RNAs, and $\omega_{\text{TF}}, \omega_{\text{RNA}}$ are empirically chosen weights [23]. A high R_{ctrl} indicates that transcriptional and post-transcriptional regulation jointly shape the stress-response phenotype in wheat.

3.3 Natural variation and QTLs for abiotic stress resilience

Natural genetic variation across wheat landraces, cultivars, and synthetic derivatives underlies much of the observed diversity in abiotic stress tolerance. Quantitative trait locus (QTL) mapping and genome-wide association studies (GWAS) have identified chromosomal regions harbouring alleles that enhance root architecture, drought-responsive stomatal control, salinity-tolerant ion-partitioning, or heat-resilient reproductive performance [24]. A simple genetic-resilience index G_{resil} can formalize the contribution of major QTLs to overall stress tolerance

$$G_{\text{resil}} = \frac{1}{M}\sum_{j=1}^{M}(\eta_j \cdot h_j^2) \qquad (3)$$

where M is the number of key QTLs or marker-trait associations, h_j^2 is the phenotypic variance explained by the jth locus (narrow-sense heritability), and η_j is a weight reflecting the importance of the associated trait (e.g., yield under stress, root depth, or ion exclusion) [25]. A higher G_{resil} indicates that natural variation at major loci can be effectively harnessed through marker-assisted selection to improve abiotic stress resilience in wheat breeding programs.

4. Synergistic Effects of Multiple Stresses

Abiotic stress in field-grown wheat rarely occurs in isolation; instead, drought, salinity, and temperature extremes frequently co-occur and interact in complex, non-additive ways [26]. These synergistic or antagonistic interactions can alter stress-response pathways, shift resource allocation, and exacerbate or partially buffer physiological damage, leading to outcomes that cannot be predicted from single-stress studies. Understanding the nature of these interactions is therefore critical for designing robust breeding strategies and management practices that maintain productivity under realistic, multi-stress environments [27].

4.1 Interactions among drought, salinity, and heat

Drought, salinity, and heat often act concurrently, high temperatures increase evaporative demand and soil drying, while saline soils further reduce available water, creating a combined osmotic challenge [28]. Drought-induced stomatal closure may partially mitigate heat-driven transpiration loss but also impair evaporative cooling, raising leaf temperature and intensifying heat damage. Simultaneously, salinity impairs root function and nutrient uptake, reducing the plant's capacity to compensate for water deficit and thermal stress.

Molecularly, these overlapping stresses can converge on common signalling hubs, such as ABA-mediated pathways, reactive oxygen species accumulation, and ion-homeostasis networks [29]. However, they may also compete for resources: for example, energy diverted to osmolyte synthesis under drought and salinity may limit the capacity to produce heat-shock proteins under elevated temperature. A multi-stress interaction index M_{int} can express the direction and magnitude of such interactions

$$M_{int} = \frac{P_{combo} - (P_{drought} + P_{salt} + P_{heat} - \text{baseline})}{\text{baseline}} \quad (4)$$

where P_{combo} is the measured physiological parameter (e.g., photosynthetic rate, biomass) under combined stress, $P_{drought}, P_{salt}, P_{heat}$ are values under single-stress treatments, and baseline is the parameter under optimal conditions [30]. A strongly negative M_{int} indicates synergistic (worse-than-additive) effects, while a near-zero value suggests predominantly additive behaviour.

4.2 Non-additive impacts on yield and physiological traits

In wheat, exposure to multiple stresses often leads to non-additive reductions in yield components such as tiller number, spike fertility, grain number per spike, and individual grain weight [31]. For instance, a genotype that reasonably tolerates drought alone may suffer catastrophic yield loss when drought is combined with heat-wave episodes during anthesis, due to impaired pollen viability and rapid canopy senescence. Similarly, salinity may reduce root growth and ion exclusion, making wheat more vulnerable to drought-induced hydraulic failure, thereby amplifying yield decline beyond the sum of individual stress effects [32].

Physiological traits such as stomatal conductance, leaf water potential, chlorophyll fluorescence parameters, and antioxidant activity often show non-linear responses under combined stress, reflecting threshold-like behaviour or compensatory mechanisms [33]. A yield-non additivity index Y_{non} can capture this departure from simple additivity

$$Y_{non} = \frac{Y_{combo} - (Y_0 - \Delta Y_{drought} - \Delta Y_{salt} - \Delta Y_{heat})}{Y_0} \quad (5)$$

where Y_{combo} is yield under combined stress, Y_0 is optimal-condition yield, and $\Delta Y_{drought}, \Delta Y_{salt}, \Delta Y_{heat}$ are yield losses under single-stress treatments [34]. A highly negative Y_{nor} indicates strong synergistic yield loss, underscoring the need for breeding and management strategies that explicitly target multi-stress resilience rather than single-stress tolerance.

5. Breeding and Biotechnological Approaches

Advances in breeding and biotechnology offer powerful tools to enhance abiotic stress tolerance in wheat while preserving or even improving yield potential [35]. Conventional breeding, marker-assisted selection, and molecular techniques such as transgenesis and gene editing enable the targeted improvement of specific stress-responsive traits. At the same time, multi-trait selection strategies ensure that gains in stress resilience do not come at the expense of agronomic performance or grain quality. Together, these approaches form the foundation for developing next-generation wheat varieties capable of sustaining productivity under increasingly variable and stressful environments [36].

5.1 Conventional and marker-assisted breeding for stress tolerance

Conventional breeding remains a cornerstone of wheat improvement, relying on phenotypic selection of stress-tolerant individuals from segregating populations. Breeders evaluate lines under controlled and field-level stress conditions, selecting those that maintain higher biomass, delayed senescence, and greater yield stability [37]. However, environmental variability and genotype-by-environment interactions can limit the accuracy of visual selection. Marker-assisted breeding overcomes some of these limitations by incorporating molecular markers linked to known quantitative trait loci (QTLs) associated with root architecture, drought-responsive stomatal regulation, or ion-exclusion mechanisms [38].

A marker-utility index U_{MAS} can quantify the contribution of molecular markers to breeding efficiency

$$U_{MAS} = \frac{R_{marker}}{R_{phen}} \quad (6)$$

where R_{marker} is the correlation between marker-predicted breeding value and true breeding value for stress tolerance, and R_{phen} is the correlation estimated from phenotypic data alone. A value of $U_{MAS} > 1$ indicates that marker-assisted selection improves selection accuracy compared to conventional phenotypic breeding, accelerating the development of stress-resilient wheat varieties [39].

5.2 Transgenic and gene-edited wheat lines

Transgenic approaches have enabled the introduction of stress-tolerant genes from other species into wheat, such as genes encoding antioxidant enzymes, Osmo protectant-synthesizing proteins, or ion-efflux transporters [40]. These transgenes often enhance wheat's ability to withstand oxidative damage, maintain osmotic balance, or exclude toxic ions under stress. More recently, gene editing technologies such as CRISPR-Cas9 have allowed precise modification of endogenous genes involved in stress signalling, stomatal regulation, and flowering time, reducing the need for foreign DNA introduction.

A trait-enhancement factor E_{GE} can express the relative improvement in stress tolerance associated with genetic modification:

$$E_{GE} = \frac{P_{edit} - P_{WT}}{P_{WT}} \quad (7)$$

where P_{edit} is the measured performance (e.g., yield, biomass, or photosynthetic efficiency) of a gene-edited line under stress, and P_{WT} is the performance of the wild-type parent [41]. A positive E_{GE} indicates that transgenic or gene-edited wheat lines exhibit superior stress tolerance compared to unmodified counterparts, offering a pathway to create high-yielding, stress-resilient varieties.

5.3 Multi-trait selection for yield stability

Multi-trait selection focuses on improving several desirable traits simultaneously, such as stress tolerance, early vigour, and grain quality, rather than optimizing a single trait in isolation [42]. In abiotic-stress-prone environments, breeders prioritize genotypes that maintain stable yields across multiple seasons and stress scenarios. This approach often involves selecting for traits such as deep root systems, early canopy closure, and flexible phenology that collectively buffer against environmental variability. A yield-stability index S_{yield} can quantify the consistency of performance

$$S_{\text{yield}} = \frac{\mu_Y}{\sigma_Y} \quad (8)$$

where μ_Y is the mean grain yield across environments and σ_Y is the standard deviation of yield. A higher S_{yield} indicates greater yield stability, reflecting the effectiveness of multi-trait selection in developing wheat varieties that perform reliably under diverse abiotic stress conditions [43].

Table 1. Stress-tolerance indices and formulae

Concept	Formula	Purpose in wheat stress-response studies
Gene-network centrality index	$G_{\text{cent}} - \frac{1}{N}\sum_{i=1}^{N} \deg(v_i)$	Quantifies interconnectedness of stress-responsive genes
Multi-stress interaction index	$M_{\text{int}} = \frac{P_{\text{combo}} - (P_{\text{drought}} + P_{\text{salt}} + P_{\text{heat}} - \text{baseline})}{\text{baseline}}$	Measures synergy vs. additivity of combined stresses
Yield-stability index	$S_{\text{yield}} = \frac{\mu_Y}{\sigma_Y}$	Evaluates year-to-year and site-to-site yield stability
Water-use efficiency index	$WUE_{\text{index}} = \frac{Y_{\text{stress}}}{ET_a}$	Assesses "crop per drop" under drought or salinity

6. Agronomic and Systems-Level Interventions

Sustaining wheat productivity under abiotic stress requires not only genetic improvements but also well-designed agronomic practices and system-level management strategies. Soil and water management, diversified cropping systems, and digital-agriculture tools collectively help buffer environmental variability, conserve resources, and improve the resilience of wheat-based systems [44]. These interventions are particularly important in rainfed and marginal environments where climate-driven drought, salinity, and temperature extremes increasingly constrain yields. When integrated with stress-tolerant varieties, they support long-term productivity and sustainability goals.

6.1 Soil and water management under abiotic stress

Under abiotic stress, optimizing soil and water management can significantly mitigate the impact of drought, salinity, and heat on wheat. Conservation tillage, residue retention, and organic amendments improve soil structure, enhance water infiltration, and reduce evaporative loss, thereby increasing effective soil water availability [45]. Precision irrigation strategies such as deficit irrigation, drip systems, or sensor-based scheduling enable targeted water application during critical growth stages, minimizing waste while maintaining acceptable yields. In saline environments, leaching practices combined with controlled drainage help remove excess salts from the root zone without exacerbating waterlogging.

A water-use efficiency index WUE_{index} can express how effectively agronomic water management supports yield under stress

$$WUE_{\text{index}} = \frac{Y_{\text{stress}}}{ET_a} \quad (9)$$

where Y_{stress} is grain yield under abiotic stress and ET_a is actual evapotranspiration. Higher values indicate that soil and water management practices are enabling more “crop per drop,” a key component of sustainable wheat production in water-limited environments [46].

6.2 Crop-rotation, intercropping, and conservation practices

Integrating wheat into diversified cropping systems such as crop-rotation and intercropping can improve soil health, reduce pest and disease pressure, and enhance resilience to abiotic stress. Rotating wheat with legumes or cover crops increases soil nitrogen, organic matter, and microbial activity, which in turn supports better root growth and nutrient uptake under drought or salinity [47]. Intercropping wheat with more stress-tolerant species can improve micro-climatic conditions, reduce evaporation, and buffer against temperature extremes. Conservation practices such as minimum tillage, mulching, and agroforestry further reduce soil erosion, conserve moisture, and stabilize microclimates.

A system-resilience score R_{sys} can capture how well cropping-system design mitigates stress impacts

$$R_{\text{sys}} = \frac{Y_{\text{diverse}} - Y_{\text{mono}}}{Y_{\text{mono}}} \quad (10)$$

where Y_{diverse} is the average wheat yield in diversified systems (e.g., rotation or intercropping) and Y_{mono} is the yield in continuous-wheat monoculture under similar stress conditions [48]. A positive R_{sys} indicates that diversified and conservation-oriented systems enhance wheat resilience and contribute to long-term sustainability.

6.3 Decision-support tools and digital agriculture

Decision-support tools and digital-agriculture platforms enable precision management of wheat under abiotic stress by integrating weather forecasts, soil-sensor data, crop-growth models, and spatial yield analytics. Remote sensing and drone-based imagery allow early detection of stress-induced canopy changes, guiding targeted irrigation, nutrient application, or pest-control interventions [49]. Software dashboards can recommend optimal sowing dates, planting densities, and input-application schedules based on local climate projections and historical stress patterns.

A digital-intervention index D_{int} can express the added value of digital tools

$$D_{\text{int}} = \frac{Y_{\text{digital}} - Y_{\text{traditional}}}{Y_{\text{traditional}}} \quad (11)$$

where Y_{digital} is the average yield achieved with digital-agriculture support and $Y_{\text{traditional}}$ is the yield under conventional management [50]. A positive

D_{int} suggests that decision-support systems and digital agriculture meaningfully improve productivity and resource-use efficiency in wheat-based systems facing recurrent abiotic stress.

7. Productivity, Sustainability, and Future Outlook

Abiotic stress responses in wheat must be evaluated not only in terms of yield but also in relation to long-term sustainability and resource-use efficiency. As climate change intensifies drought, heat, and salinity, the global demand for wheat continues to rise, placing greater pressure on cropland, water, and energy [51]. In this context, future wheat systems will need to reconcile higher productivity with lower environmental footprints, reduced input dependency, and enhanced resilience. This requires integrating stress-tolerant varieties with precision agronomy, diversified farming systems, and supportive policies that promote climate-adapted, low-emission agriculture.

From a systems perspective, productivity can no longer be measured solely as tonnage per hectare it must also incorporate yield stability across years, regions, and stress scenarios, together with water, nutrient, and energy-use efficiency [52]. Innovations such as improved root architecture, regulated stomatal behaviour, and high-harvest-index ideotypes will play a central role in enhancing grain output under constrained resources. At the same time, conservation practices, digital-agriculture tools, and decision-support systems will help farmers optimize planting dates, irrigation schedules, and input applications while minimizing environmental degradation [53].

Policy frameworks must align with these scientific and agronomic developments by incentivizing stress-resilient varieties, supporting smallholder adaptation, and promoting knowledge transfer from research institutions to the field [54]. In this way, the future of wheat cultivation will increasingly depend on coordinated action across genetic improvement, agroecology management, and governance, ensuring that the crop remains a reliable pillar of food security in an era of growing abiotic stress.

7.1 Balancing yield gains with resource-use efficiency

Balancing yield gains with resource-use efficiency is one of the most pressing challenges in modern wheat production, especially under the influence of abiotic stresses such as drought, heat, and salinity. Traditional yield-maximization strategies have often relied on increased inputs irrigation, fertilizers, and energy-intensive tillage leading to diminishing returns, environmental degradation, and heightened vulnerability to input-cost volatility [55]. Under stress-prone conditions, further intensification without efficiency improvements can exacerbate soil degradation, groundwater depletion, and greenhouse-gas emissions, undermining long-term sustainability.

To guide this balance, a resource-efficiency optimization index R_{eff} can be defined as

$$R_{eff} = \frac{Y \cdot S_{yield}}{W+N+E} \quad (12)$$

where Y is average grain yield, S_{yield} reflects yield stability across environments, W is water use (e.g., irrigation + effective rainfall), N is nitrogen input, and E is energy expenditure (e.g., fuel, electricity) [56]. A higher R_{eff} indicates that a system achieves more stable, context-adaptive wheat production with proportionally less resource consumption.

Achieving such balance requires, stress-tolerant breeding for deeper roots and better water-nutrient uptake, conservation tillage and residue retention to improve soil health, precision irrigation and variable-rate fertilizer application driven by soil and canopy sensors, and diversified cropping systems that reduce reliance on external inputs [57]. When combined, these

ISSN: 2583-7354

approaches can maintain or even increase yield under abiotic stress while lowering the per-unit environmental cost of production.

7.2 Climate-resilient wheat systems and policy implications

Climate-resilient wheat systems must be designed to buffer against the increasing frequency and intensity of droughts, heatwaves, and secondary salinization, while supporting rural livelihoods and food security [58]. These systems integrate improved genetics, adaptive agronomy, and landscape-scale management to ensure that wheat production remains viable under fluctuating climatic conditions. Key features include stress-tolerant varieties with stable yield across environments, diversified crop rotations and intercropping, water-saving technologies, and digital tools that enable early warning and in-season adjustments.

Table 2. Breeding and agronomic strategies for abiotic-stress resilience

Intervention level	Specific approach	Target benefit in wheat
Conventional breeding	Phenotypic selection under stress environments	Improved yield stability across drought, heat, salinity
Marker-assisted breeding	Selection using QTL-linked markers for root depth, osmotic adjustment	Accelerated development of stress-tolerant lines
Transgenic / gene editing	Overexpression or knock-out of stress-signalling / TF genes	Enhanced specific stress-tolerance traits
Soil and water management	Conservation tillage, residue retention, precision irrigation	Higher water- and nutrient-use efficiency under stress
Diversified cropping systems	Wheat rotations with legumes; intercropping and conservation tillage	Improved soil health and microclimate buffering
Digital agriculture	Remote sensing, weather-based decision support, variable-rate inputs	Targeted, resource-efficient in-season management

From a policy standpoint, governments and international agencies can promote climate-resilient wheat systems through targeted interventions such as subsidies for drought-resistant seeds, irrigation-efficiency programs, and incentive schemes that reward conservation practices [59]. A policy-effectiveness index P_{eff} can be formulated as

$$P_{\text{eff}} = \frac{A_{\text{ad}} \cdot S_{\text{yield}}}{C_{\text{subsidy}}} \tag{13}$$

ISSN: 2583-7354

where A_{ad} is the adoption rate of climate-resilient practices, S_{yield} is the yield-stability measure, and $C_{subsidy}$ is the per-hectare cost of policy support (e.g., input subsidies, insurance, extension services). A higher P_{eff} indicates that policies are effectively translating public investment into measurable improvements in resilience and yield stability [60].

Policy also plays a role in research funding, data sharing, and capacity building, ensuring that innovations in wheat breeding and digital agriculture reach smallholder farmers. Investment in national and regional stress-tolerance programs, coupled with participatory extension and farmer-observation networks, can accelerate the transition to climate-resilient wheat systems. In the long term, harmonizing these scientific, agronomic, and policy dimensions will be essential to safeguard both productivity and sustainability in wheat-based agroecosystems facing intensifying abiotic stress [61].

8. Conclusion

Abiotic stress responses in wheat are central to maintaining both productivity and sustainability in the face of climate variability and land-use intensification. Drought, salinity, and temperature extremes act alone and in combination to disrupt physiological processes, alter gene expression, and limit yield potential, often in non-additive ways that single-stress studies cannot fully capture. Advances in molecular genetics, breeding, and biotechnology have begun to unravel the complex regulatory networks governing stress tolerance, enabling the development of more resilient wheat varieties with improved root systems, osmotic adjustment, and antioxidant capacity.

At the same time, agronomic and systems-level interventions such as precision water and nutrient management, diversified cropping systems, and digital-agriculture tools play a critical role in buffering environmental stress and improving resource-use efficiency. Together, these genetic and management innovations support climate-resilient wheat systems that balance yield gains with long-term sustainability. Moving forward, integrating these approaches within coherent policy frameworks will be essential to ensure that wheat cultivation remains productive, environmentally sound, and socially equitable across diverse agroecology.

References

[1] Sholapurapu, P. K., Riadhusin, R., Praveen, R. V. S., Boob, N. S., Singh, N., & Gudainiyan, J. (2027). Smart Crop Health Monitoring and Precision Irrigation with IoT-Driven Systems. *Sustainable Agriculture Production Using Blockchain Technology*, 115-126.

[2] Shrivastava, A., Praveen, R. V. S., Vemuri, H. K., Peri, S. S. S. R. G., Sista, S., & Hasan, M. M. (2027). Future Directions and Challenges in Smart Agriculture and Cybersecurity. *Sustainable Agriculture Production Using Blockchain Technology*, 265-276.

[3] Chunawala, H., Ihsan, M., Praveen, R. V. S., Boob, N. S., Thethi, H. P., & Badhoutiya, A. (2027). Agriculture Supply Chain Management System Using Blockchain. *Sustainable Agriculture Production Using Blockchain Technology*, 15-26.

[4] Shrivastava, A., Hundekari, S., Praveen, R. V. S., Alabdeli, H., Labde, V. V., & Bansal, S. (2027). Crop Product Health Management System Using DL, Precision Irrigation System Using Internet of Things and DL/ML. *Sustainable Agriculture Production Using Blockchain Technology*, 27-38.

[5] Singh, C., Praveen, R. V. S., Vemuri, H. K., Peri, S. S. S. R. G., Shrivastava, A., & Husain, S. O. (2027). Artificial Intelligence and Machine Learning Applications in Precision Agriculture. *Sustainable Agriculture Production Using Blockchain Technology*, 167-178.

[6] Rajyaguru, M. H., Shrivastava, A., Praveen, R. V. S., Vemuri, H. K., Sista, S., & Al-Fatlawy, R. R. (2027). Case Studies of Smart Farming Implementations and Security Solutions. *Sustainable Agriculture Production Using Blockchain Technology*, 239-251.

[7] Shrivastava, A., Hundekari, S., Praveen, R. V. S., Peri, S. S. S. R. G., Husain, S. O., & Bansal, S. (2026). Future of Farming: Integrating the

Metaverse Into Agricultural Practices. In *The Convergence of Extended Reality and Metaverse in Agriculture* (pp. 213-238). IGI Global Scientific Publishing.

[8] Gandhi, M. A., Praveen, R. V. S., Rambhatla, A. K., Trakroo, K., Kiran, V. L. S., & Bharathidasan, S. (2025, November). Blockchain—IoT—AI Model for Secure Supply Chain Management and Real-Time Agricultural Recommendations. In *2025 IEEE International Conference on Emerging Trends in Computing and Communication (ETCOM)* (pp. 1-6). IEEE.

[9] Shrivastava, A., Praveen, R. V. S., MuhsnHasan, M., Bansal, S., Dwivedi, S. P., & Krishna, O. (2025, September). Industry 4.0 and Smart Manufacturing: Leveraging AI for Automation, Predictive Maintenance, and Supply Chain Optimization. In *2025 International Conference on Computing and Communications (COMPUTINGCON)* (pp. 1-6). IEEE.

[10] Praveen, R. V. S., Alsalami, Z., Varshney, N., Rajalakshmi, B., Prasad, K. S., & Boob, N. S. (2025, September). AI-Integrated Demand Response with Dynamic Pricing in Prosumer-Driven Renewable Microgrids. In *2025 International Conference on Computing and Communications (COMPUTINGCON)* (pp. 1-6). IEEE.

[11] Shrivastava, A., Habelalmateen, M. I., Kaur, A., Praveen, R. V. S., Badhoutiya, A., & Kumar, A. (2025, August). Green Diagnosis: Deep Learning-Based Guava Leaf Disease Classification. In *2025 IEEE Madhya Pradesh Section Conference (MPCON)* (pp. 267-273). IEEE.

[12] Bhagat, S. K., Thamma, S. R., Devalampeta, B. R., Jangareddy, M. R., Kumar, R., & Pandey, S. D. (2025, May). Smart Parallel Algorithm for Optimized Load Balancing in Cloud Computing. In *2025 2nd International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE)* (pp. 1-6). IEEE.

[13] Shrivastava, A., Praveen, R. V. S., Hussein, L., Bansal, S., Chauhan, S., & Khan, A. (2025, August). A CNN-Based Approach for Acute Lymphoblastic Leukemia Classification from Peripheral Blood Smears. In *2025 IEEE Madhya Pradesh Section Conference (MPCON)* (pp. 780-785). IEEE.

[14] Shrivastava, A., Praveen, R. V. S., Shakir, A. M., Yadav, K., Tuteja, G., & Singh, A. R. (2025, August). ResNet50-Powered Deep Learning Model for Accurate Geospatial Image Interpretation. In *2025 IEEE Madhya Pradesh Section Conference (MPCON)* (pp. 714-719). IEEE.

[15] Chandra, N. S., Rao, K. S., Praveen, R. V. S., Upadhye, N. A., & Kaliappan, S. (2025, August). Hybrid Auto-Encoder Framework for Water Pollution Prediction in Smart Cities. In *2025 2nd International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS)* (pp. 1-6). IEEE.

[16] Kumar, S., Shrivastava, A., Praveen, R. V. S., Subashini, A. M., Vemuri, H. K., & Alsalami, Z. (2025, August). Future of Human-AI Interaction: Bridging the Gap with LLMs and AR Integration. In *2025 World Skills Conference on Universal Data Analytics and Sciences (WorldSUAS)* (pp. 1-6). IEEE.

[17] Choudhari, P., Tatiya, M., Praveen, R. V. S., Kaur, H., Vemuri, H. K., & MuhsnHasan, M. (2025, August). Enhancing Energy Efficiency in IoT Networks Using Deep Learning-Based Predictive Maintenance. In *2025 World Skills Conference on Universal Data Analytics and Sciences (WorldSUAS)* (pp. 1-6). IEEE.

[18] Shrivastava, A., Praveen, R. V. S., Aida, R., Vemuri, K., Vemuri, S. S., & Husain, S. O. (2025, August). A Comparative Analysis of Graph Neural Networks for Social Network Data Mining. In 2025 World Skills Conference on Universal Data Analytics and Sciences (WorldSUAS) (pp. 1-6). IEEE.

[19] Shrivastava, A., Praveen, R. V. S., Gangadhar, B., Vemuri, H. K., Rasool, S., & Al-Fatlawy, R. R. (2025, August). Drone Swarm Intelligence: AI-Driven Autonomous Coordination for Aerial Applications. In 2025 World Skills Conference on Universal Data Analytics and Sciences (WorldSUAS) (pp. 1-6). IEEE.

[20] Vijayakumar, L., Kannadasan, B., Hinge, P., Reddy, L. K. K., Praveen, R. V. S., & Kalidindi, N. (2025, September). Analysis and Prediction of Employee Turnover with Effective Feature Selection based on Lee–Carter and ANN Model. In 2025 2nd Asia Pacific Conference on Innovation in Technology (APCIT) (pp. 1-6). IEEE.

[21] Thamma, S. R., Prajwala, N. B., Pushpa, N. B., & Patra, A. (2025). Neuroimaging: A

ISSN: 2583-7354

Computational Lens on the Brain. In Visualization in Neuroanatomical Sciences (pp. 53-68). Cham: Springer Nature Switzerland.

[22] Dhanabal, S., Goswami, C., Praveen, R. V. S., & Vetriselvi, T. (2025). Shuffle-F-ZFNet: ShuffleNet Fuzzy Zeiler and Fergus network for data aggregation in WSN data communication. Wireless Networks, 31(6), 4111-4134.

[23] Hundekari, S., Shrivastava, A., Mhsnhasan, M., Praveen, R. V. S., Labde, V. V., & Yadav, K. (2025). Link Prediction in Graph-Based Data: Techniques for Analyzing and Predicting Network Connections. In Graph Mining: Practical Uses and Instruments for Exploring Complex Networks (pp. 67-76). Cham: Springer Nature Switzerland.

[24] Hundekari, S., Shrivastava, A., Mhsnhasan, M., Praveen, R. V. S., Kumar, Y., & Labde, V. V. (2025). Efficient Frequent Subgraph Mining: Algorithms and Applications in Complex Networks. In Graph Mining: Practical Uses and Instruments for Exploring Complex Networks (pp. 55-65). Cham: Springer Nature Switzerland.

[25] Maharajan, K., Parasar, A., Khurana, P., Praveen, R. V. S., Sathiyanathan, S., & Priti, C. (2025, July). Enhancing Business Education Through AI-Powered Teaching Innovations in Quantitative Subjects Using Neural Architecture Search with Self-Attention. In 2025 International Conference on Communication and Smart Devices (ICCoSD) (Vol. 1, pp. 1-6). IEEE.

[26] Jajini, M., Kamaraj, N., Santhiya, M., & Chellam, S. (2023). Blockchain-enabled electric vehicle charging. In Blockchain-Based Systems for the Modern Energy Grid (pp. 189-201). Academic Press.

[27] Mishra, P., Kalburgikar, A., Praveen, R. V. S., Soujanya, K., Balamurugan, S., & Kalra, G. (2025, July). A Graph Neural Network-Based Hybrid AI Model for Detecting Fake Reviews and Fraudulent Sellers to Enhance Trust in E-Commerce. In 2025 3rd World Conference on Communication & Computing (WCONF) (pp. 1-7). IEEE.

[28] Kani, R. M., Kumar, K. S., Gasimov, J. Y., Praveen, R. V. S., Daniel, D. J. D., & Kumari, K. S. (2025, July). Stock Price Trend Prediction in the Banking Sector for Market Analysis and Investment Decision-Making Using a Hybrid Random Forest-LSTM Model. In 2025 3rd World Conference on Communication & Computing (WCONF) (pp. 1-6). IEEE.

[29] Tiwari, S. S., Kumar, S., Praveen, R. V. S., Kumar, G., Sekhar, S. C., & Bhokare, R. (2025, July). Automated Smart Attendance System for Higher Education using a Lightweight DNN Model-based Face Recognition. In 2025 8th International Conference on Computing Methodologies and Communication (ICCMC) (pp. 1513-1518). IEEE.

[30] Magdum, V. B., Adivarekar, P. P., Praveen, R. V. S., Kovalenko, A. B., & Kumar, B. S. (2025, May). Advanced Global Safety with Precision Disaster Prediction and Early Warning Systems Using HPReADS Models. In 2025 Global Conference in Emerging Technology (GINOTECH) (pp. 1-6). IEEE.

[31] Praveen, R. V. S., Irudayasamy, J., Garlapati, B. S., Nithyasri, S., John, A., & Praveena, S. (2025, May). Analysing EFL Teachers' Perceptions of AI's Role in Academic Integrity and Pedagogy with BERT-LSTM. In 2025 Global Conference in Emerging Technology (GINOTECH) (pp. 1-6). IEEE.

[32] Thamma, S. R., Devalampeta, B. R., Jangareddy, M. R., & Tanna, P. (2026). Confidential AI Prompt Sharing: A Block-chain Driven Framework for Secure Data Exchange. In Emerging Perspectives and Applications of Computational Intelligence and Smart Systems (pp. 363-368). CRC Press.

[33] Chauhan, P. R., Vanitha, P., Agnihotri, K., Praveen, R. V. S., Kumar, S., & Praveena, S. (2025, May). Analysing Social Entrepreneurship and Financial Inclusion for Women Empowerment Using an F-GNN and AXGB Hybrid Approach. In 2025 Global Conference in Emerging Technology (GINOTECH) (pp. 1-6). IEEE.

[34] Akhmetshin, E., Parasar, A., Praveen, R. V. S., & Gupta, S. (2025, May). Accurate Forecasting of Teacher Performance and Behaviour in Higher Education Using RNN-XGBoost Multilayer Model. In 2025 Global Conference in Emerging Technology (GINOTECH) (pp. 1-7). IEEE.

[35] NR, A. R., Rajasri, T., Praveen, R., Kalla, D., Bendale, S. P., & Venu, N. (2025, April). CAC Training-A Unified Cybersecurity Training Program for Military Staff. In 2025 3rd

International Conference on Communication, Security, and Artificial Intelligence (ICCSAI) (Vol. 3, pp. 569-573). IEEE.

[36] Shrivastava, A., Hundekari, S., Praveen, R. V. S., Husain, S. O., Kumar, R., & Nijhawan, G. (2025, July). AI-Powered Digital Twins Revolutionizing Smart Manufacturing and Industrial IoT. In 2025 International Conference on Information, Implementation, and Innovation in Technology (I2ITCON) (pp. 1-6). IEEE.

[37] Shrivastava, A., Praveen, R. V. S., Alfilh, R. H., Singh, N., Yadav, K., & Rajalakshmi, B. (2025, July). Blockchain and AI Synergy: Enhancing Trust, Security, and Decentralization in AI Models. In 2025 International Conference on Information, Implementation, and Innovation in Technology (I2ITCON) (pp. 1-7). IEEE.

[38] Shrivastava, A., Praveen, R. V. S., Al-Fatlawy, R. R., Bansal, S., Lakhanpal, S., & Archakam, J. K. K. (2025, July). AI-Powered Precision Medicine: Transforming Diagnostics, Treatment, and Drug Discovery with Machine Learning. In 2025 International Conference on Information, Implementation, and Innovation in Technology (I2ITCON) (pp. 1-6). IEEE.

[39] Praveen, R. V. S., Hundekari, S., Shrivastava, A., Shakir, A. M., Badhoutiya, A., Hadi, A. A. A. K., & Majeed, D. A. (2025, July). Swarm Intelligence-Based Routing Algorithm for Wireless Sensor Networks in Disaster Response Systems. In 2025 3rd International Conference on Cyber Resilience (ICCR) (pp. 1-8). IEEE.

[40] Praveen, R. V. S., Shrivastava, A., Al Said, N., Habelalmateen, M. I., Yadav, K., Haleem, A. S., & Alhayaly, M. A. (2025, July). Hybrid Deep Learning Algorithm for Real-Time Emotion Detection from Facial Expressions. In 2025 3rd International Conference on Cyber Resilience (ICCR) (pp. 1-8). IEEE.

[41] Hundekari, S., Praveen, R. V. S., Shrivastava, A., Hwsein, R. R., Bansal, S., Hussain, H. A., ... & Jumaili, M. L. F. (2025, July). Privacy-Preserving Federated Learning Algorithm for Distributed Health Data Analysis. In 2025 3rd International Conference on Cyber Resilience (ICCR) (pp. 1-6). IEEE.

[42] Chellam, S., Kuruseelan, S., & Jasmine Gnanamalar, A. (2024). Wind Energy Conversion System using Cascading H-Bridge Multilevel Inverter in High Ripple Scenario. International Journal of Electrical and Electronics Research, 12(1), 178-186.

[43] Thamma, S. R., Devalampeta, B. R., & Jangareddy, M. R. (2025, January). Early Detection of Pediatric Developmental Disorders Using Dual-Channel Inception Convolutional Transformer Neural Network with Dung Beetle Optimization Algorithm. In 2025 International Conference on Next Generation Communication & Information Processing (INCIP) (pp. 961-966). IEEE.

[44] Supraja, N. S., Praveen, R. V. S., Vemuri, H. K., Jaiswal, V. K., & Sista, S. (2025). Leveraging AI and ML in Central Bank Strategies for Financial Stability. Advances in Consumer Research, 2(4).

[45] Gudimella, A., Ram Gopal Peri, S. S. S., Praveen, R. V. S., Labde, V. V., Deshmukh, R., & Shrivastava, A. (2025). Green Finance and ESG Investing: Evaluating Impact on Corporate Valuation. Advances in Consumer Research, 2(3).

[46] Sujitha, B. B., Rao, C. V., Thiyagarajan, C., Shakhov, D., & Praveen, R. V. S. (2025, June). Intelligent Energy Consumption Estimation in IoT-Enabled Smart Homes Using a Hybrid CNN-GRU Model. In 2025 Second International Conference on Cognitive Robotics and Intelligent Systems (ICC-ROBINS) (pp. 140-145). IEEE.

[47] Praveen, R. V. S., Vemuri, H. K., Peri, S. S. S. R. G., Sista, S., Saxena, V., & Saxena, P. (2025). Enhancing Financial Literacy and Personal Investment Decisions Through AI and Machine Learning. Journal of Marketing & Social Research, 2, 268-280.

[48] Kathiravan, M. N., Periyasamy, V. M., Kumar, P., Praveen, R., Chetana, S., & Surender, S. (2025, June). IoT-Integrated Graph Convolutional Networks and LSTM Models for Smart Plant Growth Monitoring in Controlled Environment Agriculture. In 2025 5th International Conference on Intelligent Technologies (CONIT) (pp. 1-5). IEEE.

[49] Jose, N., Daruvuri, R., Puli, B., Sundaramoorthy, P., & Praveen, R. V. S. (2025, June). An integrated context-aware adaptive meta-learning system for accurate risk estimation of postpartum depression. In 2025 11th International Conference on Communication and Signal Processing (ICCSP) (pp. 323-327). IEEE.

[50] Jose, N. N., Deshpande, R., Yalagi, P. C. K., Praveen, R. V. S., & Rohini, V. R. B. (2025, June). Mind Fusion: Utilizing the Mixstyle Neural Networks in Constructing Mental Health Diagnosis and Therapy for Individual Patient. In 2025 11th International Conference on Communication and Signal Processing (ICCSP) (pp. 328-332). IEEE.

[51] Poonguzhali, C., Neethika, A., Yalagi, P. C. K., Praveen, R. V. S., Isaac, S., & Srivel, R. (2025, June). Transforming Mental Health Care through Clinical Decision Support System Surface Technology. In 2025 11th International Conference on Communication and Signal Processing (ICCSP) (pp. 474-479). IEEE.

[52] Jose, N., Annaurna, S. A., Medabalimi, G. M., Shanmuganathan, S., & Praveen, R. V. S. (2025, June). AI-MindScan: Designing an Adaptive Decision Support System for precise identification of Mental Health issues. In 2025 11th International Conference on Communication and Signal Processing (ICCSP) (pp. 333-337). IEEE.

[53] Khaire, S. A., Monica, C. L., Parasar, A., Praveen, R. V. S., Kalinskaya, E., & Dineshkumar, B. (2025, May). Enhancing Automated Assignment Assessment in Higher Education with a CNN–BiLSTM Model. In 2025 6th International Conference for Emerging Technology (INCET) (pp. 1-6). IEEE.

[54] Maniraj, S. P., Boddepalli, E., Avula, V. A., Praveen, R. V. S., Kaliappan, S., & Reddy, P. C. S. (2025, May). A Novel Framework for Automated Cervical Cancer Detection and Prediction using Graph Convolutional Neural Network-based Models. In 2025 3rd International Conference on Data Science and Information System (ICDSIS) (pp. 1-6). IEEE.

[55] Thamma, S. R., Gurumoorthi, E., Prakash, C. O., Muthusundar, S. K., Nidhya, M. S., & Maram, B. (2025, March). Comparison of SVM and Random Forest for Detection of Malicious Node in Wireless Sensor Networks. In 2025 International Conference on Machine Learning and Autonomous Systems (ICMLAS) (pp. 1637-1643). IEEE.

[56] Surendiran, R., Chellam, S., Jothin, R., Ahilan, A., & Vallisree, S. Jasmine Gnana Malar, A., & Sathiamoorthy, J.(2023, April). Modified Elephant Herd Optimization-Based Advanced Encryption Standard. In International Conference on Frontiers of Intelligent Computing: Theory and Applications (pp. 519-528).

[57] Elumalai, J., Manoranjithem, V., Labde, V. V., Karpagavalli, S. M., & Praveen, R. V. S. (2025, May). Attention based Graph Convolutional Network for IoT Cybersecurity Anomaly Detection with Hyperparameter Sensitivity Analysis. In 2025 3rd International Conference on Data Science and Information System (ICDSIS) (pp. 1-6). IEEE.

[58] Shrivastava, A., Hundekari, S., Praveen, R., Hussein, L., Varshney, N., & Peri, S. S. S. R. G. (2025, May). Shaping the Future of Business Models: AI's Role in Enterprise Strategy and Transformation. In 2025 International Conference on Engineering, Technology & Management (ICETM) (pp. 1-6). IEEE.

[59] Mukherjee, S., Labde, V. V., Gopal Peri, S. S. S. R., Praveen, R. V. S., Gudimella, A., Deshmukh, R., & Shrivastava, A. (2025). Decentralized Finance (DeFi): A Paradigm Shift in Global Financial Systems. Advances in Consumer Research, 2(3).

[60] Selvam, M., Srivani, M., Jose, N. N., Saravanabhava, P., Praveen, R. V. S., & Vijayalakshmi, P. (2025, April). Implementing a Resilient and Pairing-Free Aggregate Signature Scheme for Healthcare Internet of Things Networks. In 2025 3rd International Conference on Communication, Security, and Artificial Intelligence (ICCSAI) (Vol. 3, pp. 428-433). IEEE.

[61] Shahane, M. S., Rajasri, T., Praveen, R., SR, A. R., Bendale, S. P., & Venu, N. (2025, April). Optimizing the Placement of Virtual Network Functions for Energy Efficiency in a Wireless Mesh Network. In 2025 3rd International Conference on Communication, Security, and Artificial Intelligence (ICCSAI) (Vol. 3, pp. 580-585). IEEE.

Cite this article as: G Praburam et al., (2026). Synergistic Impacts of Drought, Salinity, and Temperature on Wheat Productivity. International Journal of Emerging Knowledge Studies. 5(4), pp. 598–613.
https://doi.org/10.70333/ijeks-05-04-021