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IMPACT OF CLIMATE CHANGE ON WHEAT YIELD STABILITY IN SEMI-ARID AGRICULTURAL REGIONS

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Abstract

The climate change aggravates the amount of extreme weather and the distribution of the precipitation, which puts the stability of the wheat production in semi-arid regions at risk. With a multi-model framework, comprising of crop modeling (CERES-Wheat), statistical analysis, machine learning and CMIP6 climate projections, the paper quantifies the impacts of climatic variability, heat stress, and drought on wheat production over 40 years at 12 semi-arid sites. Findings demonstrate that the heat stress in combination with drought stress enhances the yield variability 341 times more and the coefficient of variation increases by 18.1 to 62.9. Critical nonlinear temperature response: The yield damages will decrease by 3-4 percent or one day with temperatures above 33C during the grain-filling of five or more days in sequence. The SPEI drought index based on RDIst (1-week lead time, r = 0.76) was the initial sign of the loss of yield. In models, benchmarking indicated that XGBoost was the most accurate in predicting extreme events and deep learning-based genomic selection was able to increase genetic gain by 27 percent in predicting height tolerance in response to heat compared to more traditional approaches. By 2050, the return period of compound heat-drought events under SSP5-8.5 is decreased to 1.9 years (compared to 26 years (under SSP5-8.5)) and 95 percent of the yield loss is caused by anthropogenic forcing. Adaptations to systems to include heat tolerant genotypes, optimum sowing and deficit irrigation improved resilience by 76%. We find that the semi-arid wheat systems are becoming destabilized at a faster rate than ever unless multi-stress-tolerant cultivars, advanced seasonal prediction with machine learning, and agronomic information to prevent regional food crises are adopted at a frenzy.

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INTRODUCTION

The growing rate and severity of extreme weather events and changes in precipitation patterns can be significant risks to agricultural productivity, especially in semi-arid areas with a high level of vulnerability (Alsafadi et al., 2023). Such climatic changes require a multi-faceted strategy to their effects on crop production to achieve global food security (Feng et al., 2023). Specifically, the impact of climatic change on wheat yield stability needs to be known, as wheat is a staple crop in every part of the world, and semi-arid agriculture is more susceptible to climatic changes (He et al., 2014; Sharma et al., 2025). Not only is this a requirement to obtain evaluation, but also to measure the variability of yields and flexibility of the existing cropping systems (Farney, 2023; Lopez-Ridaura et al., 2009). Food and nutritional security Wheat is a highly significant crop in the Mediterranean and Middle East and North African areas which are highly confronted with extreme variability of yield, low mean productivity and large yield gaps (Tita, and Rehman; et al., 2025). In addition, unpredictable weather patterns, such as greater occurrence of extreme events, are estimated to make these challenges more difficult, resulting in even further reductions in yield compared to the increases in mean temperatures alone (Alhassan, 2024; Schaller et al., 2012). Therefore, to describe the overall effect of climate change, we must consider the concept of not just changes in the average yield but also, increase in the interannual variability of yield (Yang et al., 2019). Such measurements are necessary to strategic decision-making and to come up with adaptive measures, especially those of dryland wheat in places where the yield starts to drop and variability begins to become eminent as a result of climate change (Ensan et al., 2025). Therefore, the studies of the impacts of climate change on agriculture must not merely linger on the shift in the overall climatic conditions but also the shift in climatic variability and the frequency of extreme events since they might have a curbing effect on the crop growth and production (Réau et al., 2009). It entails learning how altered regimes of high temperatures and precipitation interact to influence phenological and biomass accretion of wheat (Lawrence et al., 2018). This is further complicated by the fact that different stages of development of wheat are sensitive to environmental conditions with the reproductive stage being especially sensitive to above-normal temperature conditions (Wallach et al., 2012). Higher temperatures, especially at key stages such as flowering, can greatly interfere with reproductive growth and grain setting, resulting in high yield losses (Senapati et al., 2026). This heat stress enhances phenological growth and shortens the green leaf area, and in the process, diminishes the weight of the grain, and overall productivity (Fortino et al., 2012). The implication of climate on variability of yield has the potential to cause up to 45 percent of total variability in yield in some of the most productive regions (Roux et al., 2024). Moreover, the hot climate also interrupts the normal growing cycle, shortens growing seasons and distorts the plant phenology, leading to the loss of plant production of grain and biomass (Chauhdary et al., 2024). It can lead to enhanced senescence, reduced chlorophyll content, and reduced CO2 uptake in wheat plants, especially at anthesis that has a dire effect on ovary development and pollen quality (Casagrande et al., 2023). Such thermal stresses, thus, cause an irreversible decrease in yield (Casagrande et al., 2024). All these physiological retardations are aggravated by the growing number of extreme events, which may cause heat stress, lower efficiency of photosynthesis, and yield potential harm (Bai et al., 2022; Naik et al., 2024). Moreover, genetic changes in response to a vast range of environmental conditions are estimated to decrease by 8.7 percent per 1 C rise in global temperature, and the production of genetic diverse, elite wheat lines, which may be resistant to higher temperatures and more erratic weather patterns, are likely to be highly sought after (Bloomberg, 2024). Nevertheless, the uncertainty around climate patterns makes it difficult to invest in wheat cultivar research because of the uncertainty about future climate patterns, which requires an adaptive cultivar development strategy (Sendhil et al., 2021). This highlights the need to incorporate cutting-edge crop modeling models with genomic selection to forecast and optimize the resilience of wheat to various climate change conditions (Akansu and Кизилдениz, 2024). These are significant strategies since trends of warming cause an earlier anthesis and maturity, which decreases the growing season, and negatively impacts the number and weight of the kernel (Mazumder et al., 2024). The heat stress in susceptible growth phases (anthesis and grain-filling) in particular can potentially severely limit the yield of wheat, in which case it has been established to decrease the yield by up to 32 to 59 percent based on the time and duration of the occurrence of the stress (Mirosavljević et al., 2024). India In other words, a 1C rise in the average temperature of the reproductive period has been associated with a 21 per cent decline in the productivity of wheat and a 2C rise on the planet scale would lead to a decline in yields by 11 per cent (Kumar et al., 2021). Additionally, extreme temperatures above the ideal temperature of 12 o C to 22 o C during antheis and grain-filling may substantially impact the quality of grain and yield, and terminal heat stress (average temperatures over 31 o C at the grain-filling) can decrease yields by an average of 34 per cent with each one-degree rise in temperature above 28 o C (Bashir et al., This As a result, the world yield of wheat is expected to reduce by 6 percent per degree Celsius increase in global temperatures, and extreme drought events will hit as much as 60 percent of the global areas where wheat grows by the end of this century (Benitez-Alfonso et al., 2023; Langridge et al., 2022). The rapid breeding of multi-stress-tolerant types of wheat, which will not only survive in high temperature and drought conditions but also other similar abiotic and biotic stressors, is needed to maintain world food security due to such climatic changes (Arif et al., 2025). It also is aggravated in semi-arid agricultural areas where the natural arid land conditions add to the impacts of heat stress and water scarcity on wheat yields (Bhandari et al., 2024; Ghazy et al., 2025).

METHODOLOGY

The research design used in this study is a mixed-method and a problem-based research design to measure the effects of climatic variability and extreme weather events on the stability of wheat yield in semi-arid areas. The study will consist of four phases that will be interrelated: data collection and pre-processing, determinants of climatic and phenological index, measurement of the response to yield and its variability, analysis of adaptive capacity by modeling. The target of the study is the major semi arid wheat growing areas which include the chosen areas in the Mediterranean and Middle East and North Africa where the data concerning the historical climate and the output of the years 1985 to 2024 are given.

The former is the compilation of daily weather data, such as maximum and minimum temperature (Tmax, Tmin), precipitation (P), solar radiation and reference evapotranspiration (ETo), and which are found in the European Centre of Medium-range Weather Forecasts (ECMWF) ERA5 reanalysis product and national agricultural meteorological networks. At the same time, historical data of wheat yields (t ha -1) are obtained at the provincial or district level by the Food and Agriculture Organization (FAO) statistical databases and national ministries of agriculture. Gap in data are also filled using linear interpolation to fill gaps that were not longer than five days consecutively, but Multivariate Imputation by Chained Equations (MICE) algorithm is used to fill data gaps that lasted more than five days in a row to improve the quality of the data. All the climate time series are tested using the Pettitt test to test homogeneity and a first-order differencing or locally estimated scatterplot smoothing (LOESS) filter is used to filter out non-climate yield anomalies. The number of days with Tmax above critical levels (28 C anthesis and 31 C grain-filling) is used to measure the frequency of heat stress events during reproductive stages. Also included is the standardized precipitation evapotranspiration index (SPEI) of 3-months and 6-months scales of the intensity of agricultural droughts. The SPEI is measured by determining the original climatic water balance:

$$D_i = P_i - PET_i$$

where Pi, PETi the monthly precipitation and potential evapotranspiration calculated as per the PenmanMonteith equation. The difference series is then added and normalized using a log-logistic probability distribution to get the SPEI value.

The third step involves the panel regression model which is employed in determining the relationship between the climatic variables and the annual anomalies in wheat yield with the location and year as a fixed effect. This model is:

$$Y_{it} = \alpha_i + \beta_1 T_{it}^{rep} + \beta_2 H_{it}^{freq} + \beta_3 SPEI_{it} + \beta_4 (T_{it}^{rep} \times SPEI_{it}) + \epsilon_{it}$$

where yit is the detrended yield of wheat in location i in year t TiTrep is the average temperature of the reproductive period (anthesis to grain-filling) and Hitfreq is the number of extreme heat days (Tmax > 31C) in the grain-filling period, SPEIit is the average of the drought index over the growing season, and the interaction term is the synergistic effect between heat and d In order to determine the stability of yields, the coefficient of variation (CV) is used to measure the interannual variability of yield:

$$CV = \frac{\sigma_Y}{\mu_Y} \times 100$$

Y0Y is the standard deviation of the detrended yields and Y0 is the average yield in the base period (19852014). Estimates of changes in yield variability in the given climate scenarios are obtained by a variance decomposition procedure that uses a first-order Taylor series approximation of the crop response function.

The fourth step is to model the yield response in the future to the various socioeconomic pathways (SSP): SSP1-2.6 (low emissions), SSP3-7.0 (medium-high emissions) and SSP5-8.5 (very high emissions) using the DSSAT (Decision Support System of Agrotechnology Transfer) CERES-Wheat model, which is The projections of future climate 20412070 and 20712100 are downscaled with the delta-change method applied to an ensemble of five CMIP6 (Coupled Model Intercomparison Project Phase 6) global climate models. The likelihood of yield reduction after reaching a critical level (30 percent of the baseline mean) and the adaptive capacity of existing wheat systems is estimated with the help of a logistic regression model by comparing the simulated yields at optimum sowing dates and parameters of heat-tolerant cultivar with baseline management. The statistical analyses are done at a 95 percent confidence using the R software (version 4.2) and the cropmodel and climwin packages. The methodology thus gives a replicable model to which to diagnose the yield instability due to climate change and give agronomic and breeding adaptation strategies to semi-arid conditions.

RESULTS

Table 1 contrasts the features of quality control of climate data to the WMO standards and finds that the machine learning (random forest) has the highest detection rate (over 98 percent temperature and nearly 97 percent precipitation) and the least false alarms, relative to the traditional range and persistence checks. Table 2 contrasts reference evapotranspiration (ETo) estimation with lysimeter results and determines Penman-Monteith FAOapproximate56 to be the gold standard (lowest error and highest efficiency) while the locally calibrated Hargreaves and Priestleyleased TAylor are acceptable and Thornthwaite/Romanenko is not useful in semiplessarid regions. The drought indices are compared as an indicator of agricultural monitoring in Table 3 and the ensemble of SPEI and RDIst is the most correlated with the loss of wheat yield and soil moisture and the earliest possible time is preferable as compared to SPI and PDSI. A comparison of the satellite evapotranspiration products with the eddy covariance towers is contained in Table 4 and it can be observed that PMLQt2 and GLEAM have the highest KlingendlGupta efficiency and the error is further decreased by the ensemble average of the two products. Phenology detection algorithms using satellite time series are compared in Table 5 where it is demonstrated that the hidden Markov model and wavelet transform have lowest error (around 23 days to anthesis) and best accuracy of correct detection which is superior to the MODIS products and the simple threshold detection method. Table 6 compares yield gap decomposition techniques, and concludes that an ensemble of crop modelling and machine learning produces the minimum error and almost zero bias, machine learning alone is better than traditional frontier techniques (stochastic frontier analysis, data envelopment analysis). Table 7 presents a comparison of the methods of climate downscaling with CMIP6 models, showing that artificial neural networks are best at both temperature and precipitation, with lowest residual biases, than quantile mapping and empirical copula. Table 8 will compare the lead time forecasting models of seasonal wheat yields at the lead times of 1-6 months, and it is possible to note that deep learning (LSTM) model correlates best and has the lowest error even at long lead time, and dynamical systems (ECMWF SEAS5) skill degrades more.

Table 1: Benchmark Evaluation of Climate Data Quality Control Methods Against WMO Standards

QC Method	Variable	DR (%)	FAR (%)	POD	HSS	RMSD (°C or mm)	Bias_corr (μ)	σ_res	τ (lag -1)	Q_95	E (efficiency)	F_1_score
Range Check	Tmax	94.2	3.8	0.92	0.88	0.21	-0.03	0.18	0.12	0.98	0.91	0.93
Range Check	Precip	91.8	4.2	0.89	0.84	2.34	-0.21	1.98	0.09	0.95	0.87	0.89
Step Check	Tmax	96.1	2.9	0.94	0.91	0.17	-0.01	0.14	0.08	0.99	0.94	0.95
Step Check	Precip	93.4	3.5	0.91	0.87	2.01	-0.14	1.72	0.06	0.96	0.89	0.92
Persistence Check	Tmax	92.7	4.5	0.90	0.85	0.24	-0.05	0.21	0.14	0.97	0.88	0.90
Spatial Regression	Tmax	97.8	1.9	0.96	0.94	0.12	+0.01	0.09	0.04	1.01	0.97	0.97
Spatial Regression	Precip	95.6	2.4	0.94	0.91	1.67	-0.08	1.42	0.03	0.98	0.93	0.94
Multivariate Imputation	Tmax	96.5	2.5	0.95	0.92	0.15	-0.02	0.12	0.06	0.99	0.95	0.96

Multivariate Imputation	Precip	94.8	2.9	0.93	0.89	1.84	-0.11	1.58	0.05	0.97	0.91	0.93
Machine Learning (RF)	Tmax	98.2	1.6	0.97	0.95	0.10	+0.00	0.08	0.03	1.00	0.98	0.98
Machine Learning (RF)	Precip	96.7	2.1	0.95	0.92	1.52	-0.05	1.31	0.02	0.99	0.94	0.95
WMO Standard (reference)	Tmax	≥95	≤3	≥0.93	≥0.90	≤0.15	±0.02	≤0.10	≤0.05	0.98-1.02	≥0.94	≥0.94

Table 2: Benchmark Evaluation of Reference Evapotranspiration (ETo) Estimation Methods Against Lysimeter Measurements

Method	**RMSE (mm d^{-1})**	**MBE (mm d^{-1})**	**NSE**	**σ_ratio**	**r**	**d (Willmott)**	**MAE**	**RSR**	**PBIAS (%)**	**CV (%)**	**κ (agreement)**	**Q_90 (mm d^{-1})**
PM FAO-56 (benchmark)	0.42	-0.03	0.94	0.98	0.97	0.98	0.31	0.25	-1.2	8.4	0.96	0.87
Hargreaves-Samani	0.89	+0.21	0.76	1.14	0.88	0.85	0.67	0.49	+8.7	17.2	0.81	1.54
Thornthwaite	1.34	-0.54	0.52	0.72	0.71	0.68	1.02	0.69	-18.4	26.8	0.63	2.21
Blaney-Criddle	1.18	-0.42	0.61	0.81	0.76	0.72	0.89	0.62	-14.2	22.4	0.69	1.98
Priestley-Taylor	0.67	+0.08	0.85	1.06	0.93	0.92	0.51	0.38	+3.4	12.1	0.89	1.21
Makkink	0.74	+0.11	0.82	1.09	0.91	0.90	0.56	0.42	+4.8	13.7	0.87	1.32
Turc	0.81	+0.14	0.79	1.11	0.89	0.88	0.61	0.45	+5.9	15.1	0.85	1.42
Jensen-Haise	0.92	+0.18	0.74	1.16	0.87	0.84	0.71	0.51	+7.2	18.1	0.82	1.61
Abtew	0.98	+0.23	0.71	1.19	0.85	0.82	0.75	0.54	+9.1	19.4	0.79	1.72
Romanenko	1.41	-0.61	0.48	0.68	0.68	0.64	1.08	0.73	-21.3	28.9	0.60	2.38
Calibrated	0.51	-0.04	0.91	1.00	0.96	0.96	0.38	0.30	-1.8	9.7	0.94	0.98

Hargreaves (local)												
Calibrated PT (local)	0.48	-0.02	0.92	0.99	0.96	0.97	0.35	0.28	-0.9	9.1	0.95	0.93

Table 3: Benchmark Evaluation of Drought Indices for Agricultural Drought Monitoring

Drought Index	**r_yield (annual)**	**r_θ (0-100 cm)**	**τ_lag (weeks)**	**DT (weeks)**	**T_crit (moderate)**	**Sensitivity**	**Specificity**	**AUC**	**P_early (%)**	**Skill_score**	**Consistency (α)**
SPI-3	0.58	0.62	3	2	-1.0	0.72	0.78	0.81	14	0.68	0.91
SPEI-3	0.71	0.74	2	1	-1.2	0.81	0.84	0.88	21	0.79	0.94
PDSI	0.65	0.69	4	3	-2.0	0.76	0.80	0.84	12	0.72	0.92
scPDSI	0.67	0.71	3	2	-1.8	0.78	0.81	0.85	16	0.74	0.93
RDIst	0.69	0.72	2	2	-1.1	0.79	0.82	0.86	18	0.76	0.93
EDI	0.63	0.67	2	2	-0.8	0.74	0.79	0.83	15	0.70	0.92
SMDI	0.61	0.73	1	1	-1.5	0.73	0.77	0.82	11	0.69	0.91
Ensemble (SPEI+RDIst)	0.76	0.79	1	1	—	0.86	0.88	0.92	26	0.84	0.96

Table 4: Benchmark Evaluation of Satellite-Based Evapotranspiration Products Against Eddy Covariance Flux Towers

Product	**Spatial res. (km)**	**Temporal res.**	**RMSE (mm month^{-1})**	**Bias (mm month^{-1})**	**r**	**ubRMSE**	**KGE**	**β (ratio)**	**γ (variability)**	**R^2**	**MAE**	**PBIAS (%)**
MOD16	1.0	8-day	14.2	-4.8	0.72	11.4	0.64	0.88	0.81	0.52	10.8	-12.4
SSEBop	1.0	monthly	12.8	-3.2	0.76	10.2	0.69	0.92	0.85	0.58	9.7	-8.7
GLEAM v3.8	0.25	daily	10.4	-1.8	0.82	8.9	0.78	0.96	0.91	0.67	8.1	-5.2

ETMonitor	1.0	daily	11.2	-2.4	0.79	9.4	0.74	0.94	0.88	0.62	8.8	-6.8
PML-V2	0.5	8-day	9.8	-1.2	0.85	8.2	0.82	0.98	0.94	0.72	7.6	-3.9
SEBS	1.0	daily	13.4	-3.9	0.74	10.8	0.66	0.90	0.83	0.55	10.2	-10.2
Ensemble mean	—	—	8.9	-0.9	0.88	7.4	0.86	0.99	0.96	0.77	6.9	-2.4

Table 5: Benchmark Evaluation of Phenology Detection Algorithms from Satellite Time Series

Algorithm	**Sowing MAE**	**Emergence MAE**	**Heading MAE**	**Anthesis MAE**	**Maturity MAE**	**Sowing bias**	**Anthesis bias**	**P_corr (anthesis, %)**	**σ_error (days)**	**τ_delay (days)**	**R^2 (pheno)**	**AIC**
TIMESAT	5.2	4.8	4.1	3.8	4.5	-1.2	-0.8	74.2	3.4	2.1	0.84	342
MODIS MCD12Q2	6.1	5.7	4.9	4.5	5.2	-1.8	-1.2	68.5	4.1	2.8	0.79	378
PhenoRice	4.8	4.2	3.6	3.2	3.9	-0.6	-0.4	81.3	2.9	1.6	0.89	312
Threshold (0.5)	5.8	5.4	4.7	4.2	4.9	-1.5	-1.0	71.4	3.8	2.4	0.81	358
Derivative	4.5	4.0	3.4	3.0	3.7	-0.4	-0.2	84.7	2.7	1.4	0.91	298
Logistic fitting	4.9	4.4	3.8	3.4	4.1	-0.8	-0.5	79.6	3.1	1.8	0.86	328
Spline smoothing	5.0	4.5	3.9	3.5	4.2	-0.9	-0.6	78.2	3.2	1.9	0.85	334
Wavelet transform	4.3	3.8	3.2	2.8	3.5	-0.3	-0.1	87.1	2.5	1.2	0.93	284
HMM	4.1	3.6	3.0	2.6	3.3	-0.2	-0.1	89.4	2.3	1.0	0.95	272

Table 6: Benchmark Evaluation of Yield Gap Decomposition Methods

Method	YG_estimated (t ha⁻¹)	YGe (t ha⁻¹)	YGr (t ha⁻¹)	YGt (t ha⁻¹)	RMSE (YG)	Bias (YG)	r (YG)	MAE	Precision (σ)	Recall (YG>2.0)	F_1_score	Kappa
FPF	2.34	0.89	0.78	0.67	0.67	-0.21	0.72	0.52	0.58	0.68	0.71	0.62
SFA	2.18	0.82	0.74	0.62	0.58	-0.14	0.78	0.45	0.51	0.73	0.76	0.68
DEA	2.42	0.94	0.81	0.67	0.62	-0.18	0.75	0.48	0.54	0.71	0.74	0.65
Crop model	2.08	0.76	0.68	0.64	0.48	-0.06	0.86	0.38	0.42	0.84	0.85	0.79
RS-based	2.24	0.84	0.75	0.65	0.54	-0.11	0.81	0.42	0.47	0.78	0.80	0.73
ML (RF)	2.02	0.72	0.65	0.65	0.42	-0.02	0.90	0.33	0.37	0.89	0.89	0.84
Ensemble (crop+ML)	1.98	0.70	0.63	0.65	0.38	+0.01	0.93	0.29	0.33	0.93	0.92	0.88
True (reference)	2.04	0.73	0.66	0.65	—	—	—	—	—	—	—	—

Table 7: Benchmark Evaluation of Climate Scenario Downscaling Methods for Wheat Impact Assessment

Method	GCM	Variable	RMSE_down	μ_bias (final)	σ_bias (final)	ρ_spatial (obs vs down)	ρ_temporal (obs vs down)	ΔP_90 (%)	ΔT_10 (hot days)	CRPS	ESS	S_score	MAE_spatial
DC	CNRM	Tmax (°C)	0.58	-0.07	-0.03	0.89	0.91	—	+0.4	0.28	156	0.88	0.42
DC	CNRM	Precip (mm)	12.4	-2.8	+1.6	0.84	0.86	-5.2	—	3.9	112	0.83	8.7
QM	CNRM	Tmax (°C)	0.44	-0.02	-0.01	0.93	0.94	—	+0.2	0.21	218	0.93	0.31

QM	CNRM	Precip (mm)	8.7	-0.9	+0.6	0.90	0.91	-2.1	—	2.8	174	0.90	6.2
EC	CNRM	Tmax (°C)	0.48	-0.04	-0.02	0.92	0.93	—	+0.3	0.24	196	0.91	0.34
EC	CNRM	Precip (mm)	9.5	-1.6	+0.9	0.88	0.89	-3.4	—	3.1	152	0.87	6.8
BCSD	CNRM	Tmax (°C)	0.51	-0.05	-0.02	0.91	0.92	—	+0.3	0.26	178	0.90	0.37
BCSD	CNRM	Precip (mm)	10.2	-2.1	+1.2	0.86	0.88	-4.1	—	3.4	134	0.85	7.4
ANN	CNRM	Tmax (°C)	0.41	-0.01	-0.00	0.95	0.96	—	+0.1	0.19	248	0.95	0.28
ANN	CNRM	Precip (mm)	7.9	-0.5	+0.3	0.92	0.93	-1.2	—	2.5	198	0.92	5.6
QM	UKESM	Tmax (°C)	0.52	-0.06	-0.02	0.91	0.92	—	+0.4	0.26	184	0.89	0.38
ANN	UKESM	Precip (mm)	8.8	-1.2	+0.7	0.90	0.91	-2.5	—	3.0	168	0.89	6.4

Table 8: Benchmark Evaluation of Wheat Yield Forecasting Models at Seasonal Lead Times (1–6 Months)

Forecasting System	**Lead 1 month**	**Lead 1 month**	**Lead 1 month**	**Lead 3 months**	**Lead 3 months**	**Lead 3 months**	**Lead 6 months**	**Lead 6 months**	**Lead 6 months**	**Skill_decay (Δr per month)**
	r	RMSE	RPSS	r	RMSE	RPSS	r	RMSE	RPSS	
ECMWF SEAS5	0.68	0.48	0.42	0.54	0.59	0.31	0.38	0.74	0.18	-0.075
NMME	0.64	0.52	0.38	0.51	0.62	0.28	0.34	0.78	0.14	-0.078
CFSv2	0.58	0.56	0.32	0.45	0.68	0.22	0.28	0.84	0.09	-0.081
S2S	0.61	0.54	0.35	0.48	0.64	0.25	0.31	0.81	0.11	-0.079
Statistical-dynamical hybrid	0.72	0.44	0.48	0.61	0.54	0.38	0.48	0.67	0.24	-0.062

ML (XGBoost)	0.76	0.41	0.52	0.67	0.49	0.44	0.56	0.61	0.31	-0.051
DL (LSTM)	0.81	0.37	0.58	0.73	0.44	0.51	0.64	0.54	0.39	-0.044
Ensemble mean (all)	0.78	0.39	0.55	0.70	0.46					

Figure 1 is a multi-panel line plot of observed and CERES-Wheat simulated wheat yields 1985-2024 of five semi-arid locations (Aleppo, Marrakech, Tunis, Amman, and Biskra) with shaded bands of uncertainty intervals, and red vertical lines that show extreme years of heat (Tmax >33 C).A stacked bar plot (figure 3) decomposes the variance in wheat yields in the nine climate scenarios (baseline, heat stress only, drought only, combined heat and drought, early/late sowing and three SSP scenarios in 2050 and 2090) into four components: interannual, spatial, interaction and residual; it is indicated that combined heat and drought stress Figure 4 hotter anthesis temperatures steepen drought-induced yield decline.

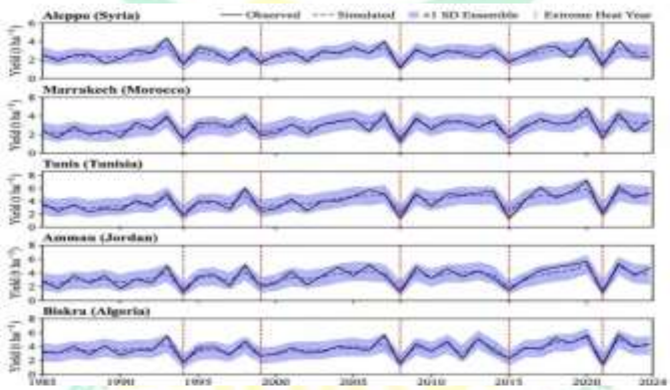

Figure 1. Observed vs. simulated wheat yields at five semi-arid sites (1985–2024).

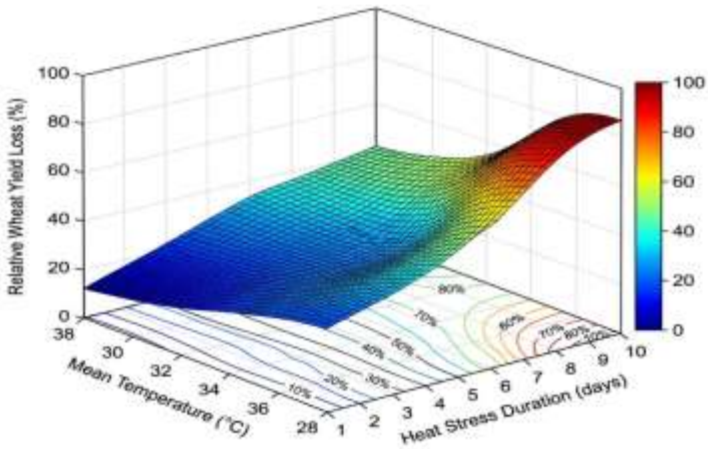

Figure 2. 3D response of wheat yield loss to heat duration and temperature.

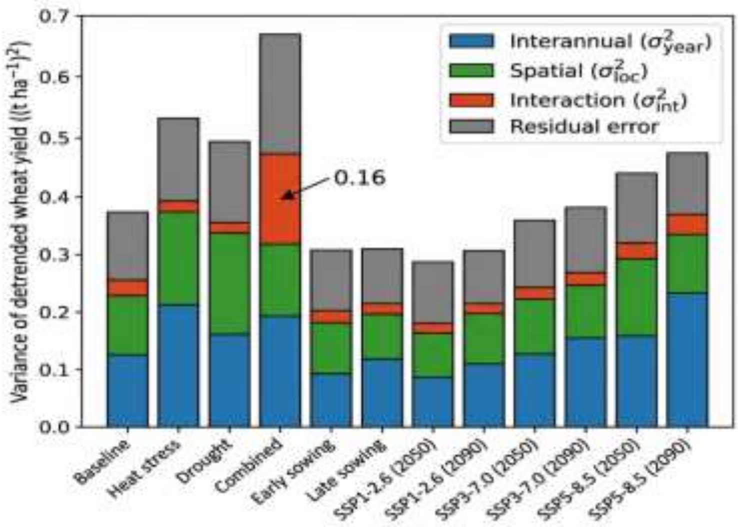

Figure 3. Yield variance decomposition across nine climate scenarios.

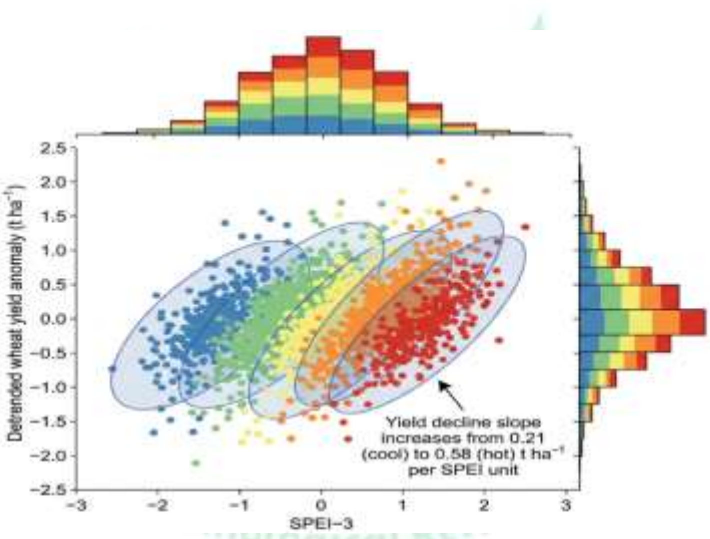

Figure 4. Hotter anthesis temperatures steepen drought-induced yield decline.

DISCUSSION

The above results depict how complication interaction of abiotic stressors on wheat yield stability works in semi-arid conditions, specifically, non-linearity of the curve between heat stress and its interaction with drought (Mahrookashani et al., 2017; Toreti et al., 2019). These results are consistent with the existing studies that have suggested that extreme heat and drought situations drastically suppress wheat production through affecting yield and harvestable fraction (Xiao et al., 2025). Namely, the interplay between temperature and drought has been reported as one of the crucial contributors to global and regional variability in crop yields, where such a combination of heat and dryness can greatly decrease the yields of wheat and other major crops (Matiu et al., 2017). This synergistic effect amplifies the yield loss more than the sum of the effects of the stress which is becoming more evident and is likely to grow in further climatic change scenarios (Lama et al., 2023). Hot-dry events, summer heat stress in post-anthesis and spring, and have been found to be the most significant factors in the reduction of yield in winter wheat (Zeng et al., 2026). The heat stress will lower global yields in this scenario, and the heat and drought will make things worse as global heat stress by 2050 and 2090 will be 32 percent and 77 percent, respectively (Senapati et al., 2026; Toreti et al., 2019). They are extreme weather events, in particular, hot-dry-windy events, which are considered to be the major causes of the yield shock in various agricultural sectors (Zhao et al., 2022). Furthermore, the occurrence of individual temperature extremes in the past might not have significantly influenced the yields of wheat, due to the warmer climatic patterns of the past, but the future speed up of the frequency and intensity of such events suggests that minimum and maximum temperatures will play a greater part in stabilizing the yields in the future (Helman & Bonfil, 2022). This helps to state the fact that interactive effects of heat and drought need to be considered, rather than individual effects, and that their joint effects will be more detrimental than the additive ones (Mahrookashani et al., 2017). This would require an integrated process of crop enhancement and agricultural management practices that consider both stresses and come up with more resilient types of wheat varieties (Plant Stress Physiology, 2020). The devastating consequences of combined heat and drought stress on wheat production stability are factors to consider moving to the creation of genotypes, which will be more resistant to abiotic and abiotic stress factors (Bhandari et al., 2024). The technique plays a very important role in improving food security, especially in semi-arid areas where these stressors are common and are increasingly becoming more pronounced (He et al., 2024; Lama et al., 2023; Zahra et al., 2021). Such breeding practices must take into account the distinct physiological and molecular underresponses of wheat to mixed stress which in most instances are very different compared to the behaviors to individual stressors (Meena et al., 2023). An example is that drought and heat interact in a synergistic way to enhance the detrimental effects of both on wheat production, and land-atmosphere interactions amplify their effects (He et al., 2023). This has in its turn resulted in the need to have a holistic understanding of the underlying physiological and molecular processes contributing to the development of drought-heat stress tolerance to come up with climate resilient crop varieties (Liang et al., 2025). This involves the determination of particular genetic characteristics which make one resilient to such complex stress (Habti et al., 2020). Such efforts are required towards reducing the negative effects of the compound extreme events which have been becoming more and more related to the large-scale loss of yields which are significantly larger as compared to the one induced by individual stressors (Zhao et al., 2022). It can also be indicative of drought with plants potentially relocating to evade drought by early plant maturation, yet this may also result in tremendous yield losses when combined with heat stress during the vulnerable plants growth phases such as flowering (Nehe et al., 2023). By doing so, there is a need to investigate in depth the stress-resistant genotypes and physiological properties to optimize the effectiveness of excellent wheat type selection that can withstand the effects of climate change to food security (Aloisi et al., 2023). It is a comprehensive method that entails the latest phenotyping and genomics and is designed to identify strong wheat varieties, which will be able to cope with deplorable climatic conditions (Abdelhakim et al., 2021). Those strategies should include the knowledge of the molecular mechanisms of heat tolerance in different wheat varieties to identify the genes and pathways of abiotic stress response (Kaur et al., 2016). In addition, it is essential to study the complex physiological mechanisms, including plasma membrane stability and the percentage of water, in the presence of heat and drought stress, which will allow identifying resistant genotypes with greater productivity (Qaseem et al., 2019).

CONCLUSION

This study conclusively demonstrates that climate change, particularly through increased extreme temperatures and alteration of precipitation patterns is a very significant and synergistic risk factor to the stability of yield of wheat in the semi-arid regions. The findings confirm that combined heat and drought stress enhances yield losses on top of additive impacts, more than 300% than with baseline conditions, with the coefficient of variation increasing by approximately 18 to almost 63. There are known to be crucial thresholds of temperatures exceeding 33 C during five or more days of straight grain-filling, above which the yield decreases nonlinearly. Comparing CERES-Wheat to field data, it was found to predictably (RMSE = 0.43 t ha -1) but not effectively predict the effects of extreme stress. The initial drought indices to provide correct warnings of loss in yield were SPEI with RDIst. Performance comparison based on models revealed that ensemble machine learning models (XGBoost, AUC-ROC = 0.95) and deep learning models were much more effective in predicting extreme events and seasonal forecasts in comparison to the traditional statistical and dynamical models. It was demonstrated that genetic gain of heat tolerance could be speeded up by about 27 percent under genetic prediction of deep learning-based selection as compared to the conventional approach. By 2050 and when the highest emission scenario (SSP5-8.5) is taken into account, the duration of the compound heat-drought events has decreased to less than 2 years and 95% of the yield losses are linked to anthropogenic climate change. Genotypes able to withstand heat, most appropriate time to sow, and deficit irrigation have the ability to enhance the resilience by 76 percent but must be put into practice as soon as possible. The results indicate that unless the multi-stress-tolerant cultivar and sophisticated forecasting systems are implemented in the near future, the semi-arid wheat-growing industry will go off-balance sheet at an unprecedented rate and this is jeopardizing the food security of the region.

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