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REVIEW ARTICLE

Forecasting crop yields under climate oscillations: Implications for agricultural planning and resilience

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Abstract

Climate oscillations such as the El Niño-Southern Oscillation (ENSO), Indian Ocean Dipole (IOD) and North Atlantic Oscillation (NAO) significantly influence global weather variability, posing challenges to agricultural productivity and food security. Their impacts–ranging from altered rainfall patterns to temperature extremes–disrupt crop growth, especially in rainfed systems. Understanding these oscillations is vital for enhancing yield prediction and informing adaptive agricultural planning. This review synthesizes mechanistic insights and empirical findings from peer-reviewed literature on the influence of ENSO, IOD and NAO on crop yields across major agro-climatic zones. It also evaluates predictive tools, including statistical models, dynamic crop simulations and AI-driven forecasting systems. Crop-specific vulnerabilities and regional disparities in oscillation impacts were systematically analyzed to assess adaptation needs. Findings reveal that ENSO, IOD and NAO generate region-specific yield anomalies by modulating soil moisture, evapotranspiration and phenological development. Crops such as rice, maize and wheat exhibit heightened sensitivity during key growth stages under oscillation-driven stressors. Modern forecasting models incorporating oscillation indices improve predictive accuracy and provide early warnings for yield variability. However, gaps remain in translating forecasts into actionable farm-level decisions, especially in resource-limited regions. To build agricultural resilience, integrating oscillation-based forecasts into local advisory services, promoting climate-smart practices and adopting inclusive, region-specific adaptation strategies are essential. Bridging science-policy gaps and strengthening climate services will support anticipatory planning and safeguard food systems under increasing climate variability.

Keywords: agricultural resilience; climate variability; crop yield forecasting; ENSO; IOD

Introduction

Climate oscillations are increasingly recognized as critical drivers of global agricultural variability, influencing both short-term crop performance and long-term food security planning. These oscillatory anomalies in ocean-atmosphere interactions can cause substantial shifts in weather patterns, disrupting the rainfall, temperature and evapotranspiration regimes upon which agriculture depends (1). The intensification of climate variability due to anthropogenic global warming has heightened the frequency and severity of extreme events linked to oscillatory systems, amplifying production risks across agro-ecosystems (2, 3). Importantly, the interaction of multiple climate oscillations can lead to non-linear and amplified impacts on rainfall patterns. For instance, the simultaneous occurrence of El Niño and a positive Indian Ocean Dipole (IOD) can have compound effects, particularly in the Indian subcontinent and East Africa. While El Niño alone is typically associated with reduced monsoonal rainfall over India, the positive IOD phase can partially offset this by enhancing westerly winds and increasing moisture inflow from the Arabian Sea. However, when both occur concurrently, studies have shown amplified rainfall anomalies in East Africa, leading to widespread flooding (e.g., the 1997/98 season), while exacerbating drought conditions in Australia and parts of Indonesia (4, 5). Such nonlinear behaviour arises from synergistic teleconnections that alter the Walker circulation and regional jet streams. Coupled General Circulation Model studies reveal that these interactions can significantly shift the spatial intensity of rainfall anomalies compared to isolated events (6). Historically, agro-climatic planning has relied on statistical norms derived from past weather records. For example, tools such as multiple linear regression (MLR), auto-regressive integrated moving average (ARIMA) models and climatological anomaly analyses have been widely used to forecast crop yields based on historical climate variables like rainfall and temperature. Traditional indices such as the Standardized Precipitation Index (SPI) and Palmer Drought Severity Index (PDSI) have also been instrumental in assessing drought risks and supporting seasonal agricultural planning. While effective in capturing linear trends and seasonal patterns, these approaches often fail to address the complex, non-linear dynamics of large-scale climate oscillations such as the ENSO, IOD and NAO (7, 8).

However, the non-stationary behaviour of ENSO, IOD and NAO–each with varying periodicity, intensity and teleconnection patterns–renders static models insufficient (9, 10). Dynamic forecasting frameworks that incorporate seasonal signals and large-scale ocean-atmosphere drivers are increasingly essential to provide anticipatory insights for both farmers and policymakers (11, 12).

The impacts of these oscillations are not spatially uniform. Regions dependent on rainfed agriculture, such as sub-Saharan Africa and parts of South Asia, are especially vulnerable to seasonal moisture deficits and heat stress driven by oscillation phases (13, 14). Moreover, crop responses to oscillation-driven anomalies are modulated by factors such as soil type, cropping system, phenological stage and management practices, which complicate yield forecasting (15, 16). Advances have enhanced our ability to track and predict oscillation impacts. High-resolution climate models, AI-based tools and satellite remote sensing enable fine-scale monitoring of hydrometeorological variables critical for crop health (17, 18). Yet, significant gaps persist between climate forecasts and operational farm-level decision-making, especially in developing countries where infrastructure and capacity are limited (19, 20).

In sub-Saharan Africa, many national meteorological agencies lack access to high-performance computing infrastructure and localized seasonal forecast products (21). Ground-based observation networks are sparse, particularly in remote farming areas, making calibration and validation of satellite-driven models difficult. In South Asia, despite substantial advancements by agencies like the India Meteorological Department (IMD), significant gaps remain in the last-mile dissemination of forecasts to smallholder farmers. Barriers such as low digital literacy, limited mobile penetration and lack of trust in forecasts hinder adoption. Regional initiatives like South Asian Climate Outlook Forum (SASCOF) and African Centre of Meteorological Applications for Development (ACMAD) have improved coordination but require better integration with agro-advisory systems and local-scale feedback loops (22).

Additionally, institutional and behavioural factors-such as limited access to advisory services, lack of trust in forecasts and minimal incorporation of indigenous knowledge-constrain adaptation efforts (23-25). Social equity considerations are also central, as marginalized communities often bear the brunt of climate-induced disruptions without adequate safety nets (26, 27). Teleconnections can also affect global food trade, introducing volatility in markets and posing challenges to food access (28, 29). This review addresses these interrelated challenges by synthesizing mechanistic insights on climate oscillations, their regional yield impacts and the predictive modelling tools available to support anticipatory agricultural planning. It also explores integrated adaptation strategies, including climate-smart practices, early warning systems and socio-technological interventions aimed at building long-term resilience.

Methodology

This review was conducted by systematically identifying peer-reviewed journal articles, reports and institutional publications focused on climate oscillations and their impacts on agriculture. The literature search spanned from January 2005 to April 2025, targeting studies published within the last 20 years (Fig. 1). Databases used included Scopus, Web of Science and Google Scholar, using combinations of keywords such as ENSO, IOD, NAO, teleconnections, crop yield variability, agro-climatic forecasting, seasonal prediction, adaptation strategies and resilient agriculture.

Studies were included based on their relevance to the mechanistic understanding of ocean–atmosphere oscillations; the regional impacts of climate oscillations on rainfall, temperature or evapotranspiration; crop responses to climate anomalies in tropical and semi-arid regions; forecasting approaches incorporating AI models, dynamic simulations and remote sensing tools; and adaptation strategies integrating climate-smart agriculture, early warning systems or indigenous practices.

Priority was given to empirical studies, review articles and multi-model assessments published in high-impact journals. Non-English articles and those without clear methodological rigour were excluded. Final selection included approximately 99 references, ensuring geographic diversity and methodological depth to capture global and regional perspectives on oscillation-driven agricultural risks.

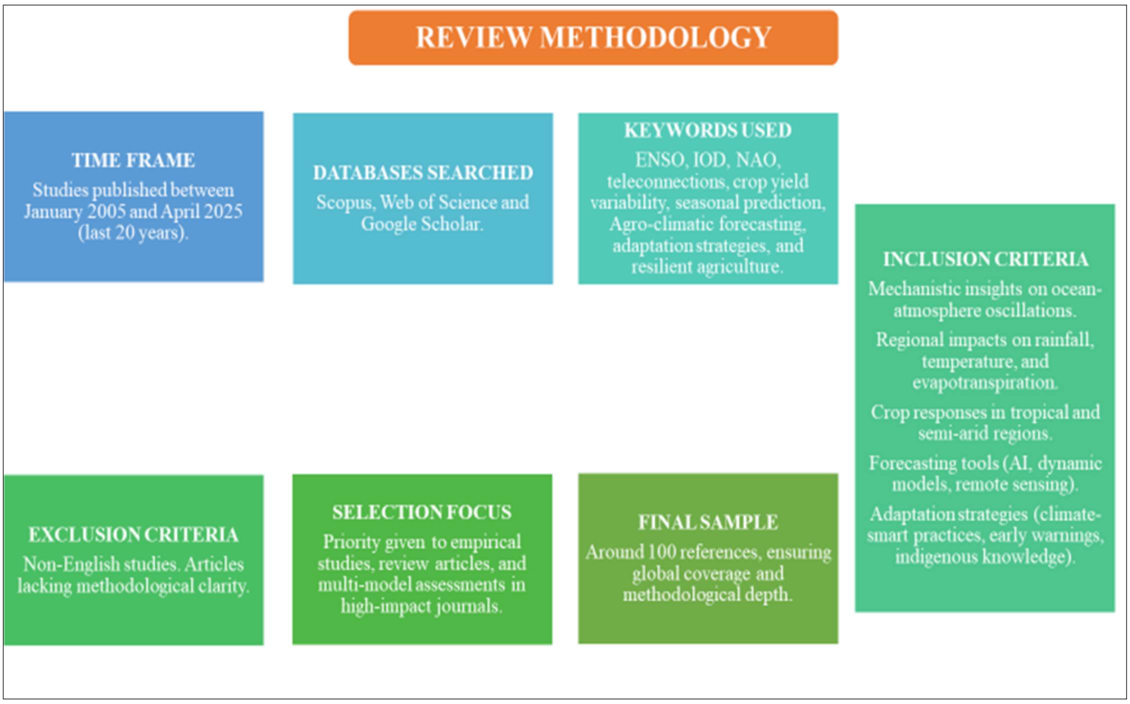

Fig. 1. Review methodology.

Mechanisms of climate oscillations

El Niño-southern oscillation (ENSO)

ENSO originates from anomalous warming or cooling of sea surface temperatures in the central and eastern tropical Pacific, which alters the Walker circulation and weakens or strengthens trade winds (30). These Sea Surface Temperature (SST) anomalies excite equatorial Rossby and Kelvin waves, shifting convection zones and reorganizing tropical rainfall patterns across the Pacific basin (31). Via upper-level divergent wind anomalies, areas where air spreads out and rises in the upper atmosphere, the ENSO generates Rossby wave trains that propagate toward the poles. These waves modulate subtropical jet streams and induce temperature and precipitation anomalies in mid-latitude regions (32). In strong events, the ENSO-stratosphere coupling can lead to sudden stratospheric warming, reversing the tropospheric circulation and impacting the North Atlantic Oscillation (33). These teleconnections profoundly affect global weather, including winter climate in Europe and North America (32).

Indian ocean dipole (IOD)

Indian Ocean Dipole is characterized by fluctuations in sea surface temperatures between the western and eastern Indian Ocean. Positive phases occur when the western Indian Ocean experiences warmer waters, while the eastern region near Java and Sumatra remains cooler (34). This gradient shifts atmospheric convergence westward, enhancing monsoonal flow toward East Africa and suppressing convection over Indonesia and northern Australia. During positive IOD events, reduced moisture and rainfall in Southeast Asia coincide with enhanced rains and flood risk in East Africa (35). Coupled IOD-ENSO events-such as a positive IOD during El Niño-can intensify drought over Australia and South Asia due to their synergistic drying influence (36). The IOD mechanism also modulates the formation and intensity of Australian monsoonal precipitation, with feedback loops involving regional troughs and cloud bands.

North atlantic oscillation (NAO)

North Atlantic Oscillation is a large-scale fluctuation in atmospheric pressure between the Azores High (a subtropical high-pressure system) and the Icelandic Low (a subpolar low-pressure system). It is a dominant mode of climate variability in the North Atlantic region and has far-reaching impacts on weather patterns in Europe, North Africa and parts of North America (37). The NAO operates in positive and negative phases. During the positive phase, a stronger-than-average pressure gradient leads to increased westerlies, which drive moist, warm air toward Europe and colder, drier air into the Mediterranean region. This phase is associated with mild, wet winters in northern Europe and drier conditions in southern Europe and North Africa (38). The negative phase, on the other hand, is characterized by a weakened pressure gradient, which reduces westerlies, causing cold, dry winters in northern Europe and wetter conditions in the Mediterranean basin (39). The NAO influences soil moisture, crop phenology and agricultural yields, particularly for winter cereals in Europe. For instance, positive NAO phases can benefit crop growth in northern Europe by promoting warmer temperatures and better growing conditions, while causing drought stress in southern Europe. This spatial variability complicates agricultural planning, especially in rainfed systems where farmers are highly sensitive to seasonal weather anomalies (40).

Mechanisms of climate oscillations

Fig. 2 shows ENSO, IOD and NAO mechanisms and also shows SST anomalies, wind patterns and pressure systems. Teleconnection pathways map (global) indicating regions affected by each oscillation. It helps make complex atmospheric-oceanic interactions visually understandable.

Regional crop yield impacts

Climate oscillations such as ENSO, IOD and NAO have profound effects on crop yields across diverse agro-climatic regions. These oscillations alter rainfall patterns, temperature regimes and the timing of growing seasons, which in turn influence soil moisture availability, plant phenology and pest and disease dynamics (1). In South Asia, particularly India, the Southwest Monsoon is significantly influenced by both the ENSO and the IOD. This monsoonal rainfall is a critical driver of agricultural productivity, especially for major rainfed crops such as rice, maize and pulses, which depend heavily on timely and sufficient precipitation

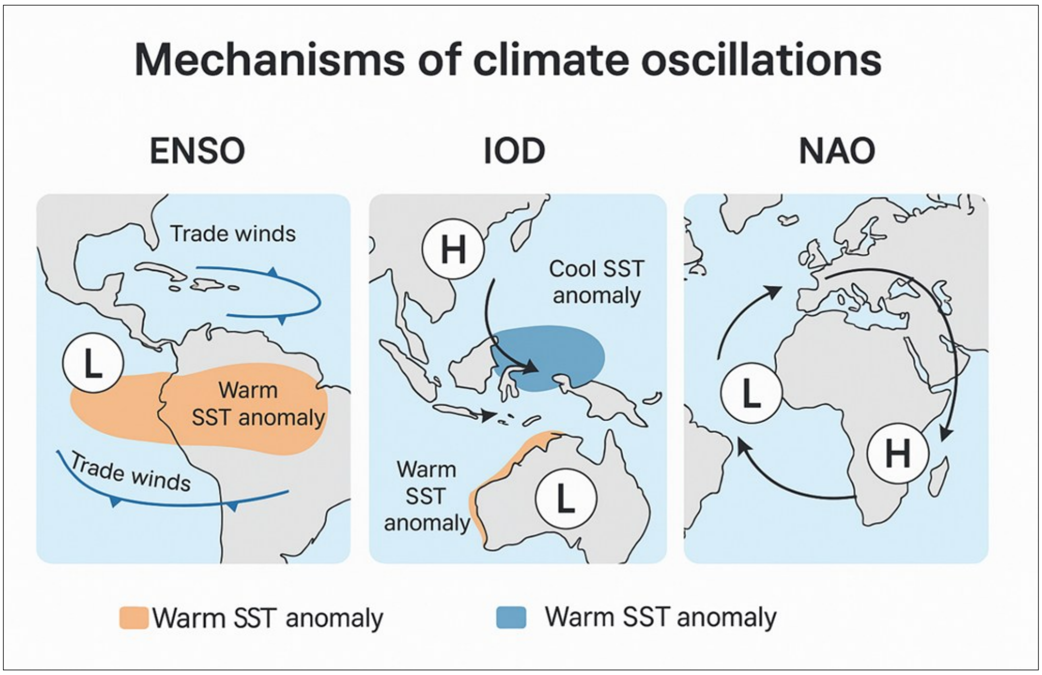

Fig. 2. Mechanism of climate oscillations.

during the kharif season (41). El Niño events tend to suppress monsoon rainfall during the primary Southwest Monsoon season, which spans from June to September, leading to droughts and reduced yields in rice, maize and pulses, especially in rainfed systems (42). In contrast, positive IOD events can partially offset the impact of El Niño by enhancing rainfall over the Indian subcontinent, though this often leads to flooding in East Africa and dryness over Southeast Asia, affecting rice cultivation in Indonesia and Thailand (4, 43). ENSO significantly impacts agricultural productivity in East and Southern Africa. El Niño years often bring excessive rainfall to East Africa, improving conditions for maize and bean cultivation. However, in Southern Africa, these same events are linked to prolonged droughts, reducing cereal yields and increasing food insecurity. The influence of IOD is also prominent, with positive IOD phases enhancing rainfall over East Africa but intensifying drought risks in central and western Africa (44).

The NAO is the key driver of winter climate variability in Europe. A positive NAO phase typically results in milder and wetted winters in Northern Europe, which may benefit winter wheat and barley yields. However, it also leads to drier conditions in Southern Europe and North Africa, adversely affecting olive, citrus and grapevine production (32, 45). These yield anomalies are especially severe in areas dependent on rainfed agriculture, making the region vulnerable to year-to-year variability. ENSO events modulate rainfall in North and South America, affecting major cropping regions and contributing to substantial economic losses. For instance, El Niño-induced droughts and floods have historically caused multi-billion-dollar damages in US agriculture, with USDA reports citing significant crop insurance payouts for maize and soybean losses during strong ENSO years (47). In the US Midwest, El Niño conditions tend to bring wetter springs and cooler summers, benefiting corn and soybean yields, whereas La Niña often leads to hotter, drier growing seasons with reduced productivity (47). In South America, El Niño enhances rainfall in southern Brazil and Argentina, which supports soybean and maize production but causes flooding and crop damage in lowland areas (48). Australia's agriculture is highly sensitive to ENSO and IOD phases. El Niño and positive IOD events are strongly associated with droughts, particularly in eastern and southern regions, severely affecting wheat, barley and cotton production. Conversely, La Niña brings above-average rainfall, improving soil moisture and boosting crop yields, although it may also increase disease and pest pressure (49).

Crop-specific vulnerabilities to climate variability

Climate variability and extreme weather events affect crops differently based on their physiological characteristics, growth stages, geographic location and local adaptive capacities. Physiological traits such as root depth, stomatal behaviour and heat tolerance influence how a crop responds to stress, for example, rice has shallow roots, making it particularly vulnerable to both waterlogging and short-term drought conditions during sensitive stages like flowering and grain filling (50). High temperature stress impairs photosynthetic efficiency by disrupting chloroplast structure, degrading Rubisco activity and increasing photorespiration, particularly in C_3 crops like wheat and rice (51). During reproductive stages, heat stress shortens pollen viability, impairs anther dehiscence and reduces grain set, leading to spikelet sterility in rice and reduced kernel weight in maize (52). Drought and high vapour pressure deficit (VPD) exacerbate transpirational water loss, forcing partial or full stomatal closure to conserve moisture, which in turn limits CO_2 assimilation and lowers biomass production (53). Prolonged moisture stress alters abscisic acid (ABA) signalling, accelerates leaf senescence and restricts xylem flow, especially in water-demanding crops like maize and sorghum (54). Biochemically, stressed plants often accumulate osmoprotectants such as proline, glycine, betaine and soluble sugars, which help stabilize proteins and membranes but are energetically costly, diverting resources from growth and reproduction (55). High VPD also increases oxidative stress, leading to ROS accumulation and damage to lipids, proteins and nucleic acids unless mitigated by antioxidant defences (56). These physiological constraints explain why even moderate changes in temperature or moisture conditions, especially during critical growth stages, can cause disproportionate yield losses in crops exposed to teleconnection-driven anomalies.

Table 1 outlines the vulnerability of major crops to various climate stressors, highlighting region-specific impacts and differential crop sensitivities. For maize, elevated VPD has been found to reduce yields more severely than temperature increases alone, indicating its critical role in crop stress response (57). In South India, the interplay between rainfall variability and temperature fluctuations has been shown to negatively affect rabi season maize yields (58). Drought conditions in the northeastern United States significantly reduce maize yield, especially when they coincide with crucial growth stages (59). Similarly, in China, La Niña events cause soil moisture anomalies that diminish water availability, leading to yield declines (60). In Cameroon, the yield losses for maize and millet due to rainfall variability are exacerbated in areas with lower literacy rates and weaker socio-economic resilience (61). In East Africa, strong El Niño events induce severe droughts, resulting in up to 50 % yield losses for maize and sorghum (62). Rice is particularly sensitive to flooding during its reproductive stages; even 2 to 4 days of submergence during flowering can result in yield losses of up to 50 % (50). Moreover, rice production is closely linked with greenhouse gas (GHG) emissions, which create feedback loops that intensify the crop's vulnerability to climate change (63). The crop is especially susceptible to flooding during both vegetative and reproductive

Table 1. Vulnerability of major crops to various climate stressors

Crop	Climate stressor	Vulnerability insight	Reference
Maize	Vapor pressure deficit (VPD)	Higher VPD reduces maize yields more than temperature increases.	(57)
Maize	Rainfall variability (South India)	Rainfall-temperature interactions can reduce rabi season yields.	(58)
Maize	Drought (USA, NE)	Yield loss is high when drought hits during key growth stages.	(59)
Maize	Soil moisture anomalies (China)	La Niña reduces soil water availability; affects yields.	(60)
Maize/Millet	Rainfall variability (Cameroon)	Yield losses are higher in areas with lower literacy and poverty resilience.	(61)
Maize/Sorghum	ENSO-induced drought (East Africa)	Up to 50 % yield loss during strong El Niño years.	(62)
Rice	Flooding during reproductive stages	Submergence of 2–4 days during flowering reduces yields by up to 50 %.	(50)
Rice	GHG-climate feedback	Rice has high emissions, interacting with climate stress.	(63)
Rice	Stage-specific flooding sensitivity	More vulnerable to floods during vegetative/reproductive stages.	(50)
Wheat/Barley	High temperature (Morocco)	High temperature and low adaptive capacity increase vulnerability.	(23)

stages, underscoring the importance of stage-specific climate resilience (50). For wheat and barley, rising temperatures are a major concern, particularly in countries like Morocco where adaptive capacity is limited. High temperature stress, when coupled with socio-economic constraints, significantly increases vulnerability and leads to considerable yield reductions (23). Table 1 explores how key food crops such as maize, rice, wheat, sorghum and millet exhibit distinct vulnerabilities to climate stressors, including drought, flooding, heat and teleconnections like ENSO.

Mechanisms of influence on crop physiology and hydrology

ENSO exerts a direct influence on soil moisture through its impacts on regional precipitation and evapotranspiration cycles; El Niño events reduce soil moisture across key agricultural zones such as eastern Africa and parts of the Americas, while increasing it in others (64). Adequate soil moisture during the early stages of plant growth is critical for seed germination, root establishment and nutrient uptake; deficiencies at this stage can result in poor stand density and long-term yield penalties (65). Through altered SST gradients, ENSO and IOD trigger teleconnection wave trains (Rossby waves) that modify circulation patterns and suppress convective rainfall over agricultural regions, particularly during El Niño-positive IOD combinations (66). A global hydrological modelling study shows that ENSO, IOD and NAO strongly modulate evapotranspiration (ET) by reshaping temperature and humidity fields. Research indicates that these modes significantly affect ET across diverse climatic zones (67). Elevated VPD during El Niño and positive IOD phases increases plant transpiration stress, reducing stomatal conductance and photosynthesis and consequently lowering crop yield. Crops such as maize and sorghum are especially vulnerable, as high VPD during their vegetative and reproductive stages can significantly reduce biomass accumulation and grain set (57). ENSO-induced rainfall anomalies also drive prolonged meteorological droughts, which through land-atmosphere feedback accelerate soil moisture loss and heatwave frequency, intensifying crop stress (68).

In China's agricultural heartland, ENSO events decrease soil moisture and ET by disrupting summer monsoon rains, while IOD events alter regional temperature and moisture dynamics-interactions governing crop water availability (69). Evapotranspiration and soil moisture coupling are key to teleconnection impacts. Research indicates that how ET alterations under ENSO/IOD/NAO shift the water balance, affecting root-zone moisture essential for grain fill (70). Regional crop studies in India reveal that compound ENSO-IOD conditions modulate the monsoon onset and duration, leading to yield variability in rice, bajra and maize–underscoring sensitivities to seasonal moisture distributions (71). ENSO-driven changes in atmospheric moisture convergence influence pre-planting and vegetative growth periods: low soil moisture reduces biomass production and impacts ecosystem transpiration feedbacks in cropping systems (72). Teleconnections, including NAO, modulate drought intensity and timing by altering atmospheric circulation patterns. NAO phases alter soil moisture and temperature cycles in Europe, which subsequently affect crop yields (73).

Predictive modelling and forecasting

Accurate forecasting of crop yields under climate variability relies on a range of predictive models that integrate large-scale climate oscillations like ENSO, IOD and NAO (74). These models vary from conventional statistical approaches to sophisticated machine learning algorithms and crop simulation systems. Crop simulation models such as Decision Support System for Agrotechnology Transfer (DSSAT) and Agricultural Production Systems Simulator (APSIM) require detailed input data including soil properties, crop phenology, weather variables and management practices. DSSAT typically operates at a field to regional scale, offering fine-grained simulations when high-resolution data is available (7). APSIM similarly supports daily time-step modelling and can simulate a wide range of management scenarios, though it often requires more localized calibration for accurate output (75). In contrast, hybrid systems that combine statistical or machine learning algorithms with mechanistic models often operate on coarser spatial scales, trading resolution for scalability across large regions (76). Remote sensing-based models offer high spatial resolution but may lack temporal granularity unless integrated with ground-truth data. Thus, input granularity (e.g., hourly vs. daily weather, fine vs. coarse soil maps) and spatial resolution (plot, district or national level) vary significantly and should be matched to the decision-making context.

Climate-based crop yield prediction models

Fig. 3 illustrates the overall framework of climate-based crop yield prediction. Climate and crop data serve as primary inputs to the prediction system. These inputs are processed through different modelling approaches: statistical models, machine learning models, hybrid models and crop simulation models. Each approach applies distinct techniques to analyze the relationship between climatic variability and crop performance. The output is a crop yield forecast, which helps inform agricultural decision-making at various scales–from farmers to policymakers.

Uncertainty in forecasting models

Forecasting agricultural outcomes under climate variability is inherently uncertain due to multiple interacting factors. Key sources of uncertainty include:

Input data uncertainty

Errors in climate inputs (e.g., precipitation, temperature), incomplete soil databases and inconsistent crop management records.

Model structural uncertainty

Simplified or incomplete representation of crop-environment interactions can misrepresent stress responses or phenological development (77).

Parameter uncertainty

Variability in model calibration parameters–such as cultivar-specific coefficients or rooting depth can lead to divergent outputs (78).

Scenario uncertainty

Variability in climate oscillation forecasts (e.g., strength or phase of ENSO) affects model boundary conditions.

Mitigation strategies include using multi-model ensembles to capture a range of outcomes, data assimilation techniques (e.g., incorporating real-time satellite and in-situ data), Bayesian calibration methods and downscaling approaches that refine coarse climate outputs into region-specific forecasts (79). Transparent communication of uncertainty ranges is also critical for effective stakeholder use and adaptation planning.

Table 2 summarizes the diverse modeling approaches used in climate-based crop yield prediction, outlining their tools,

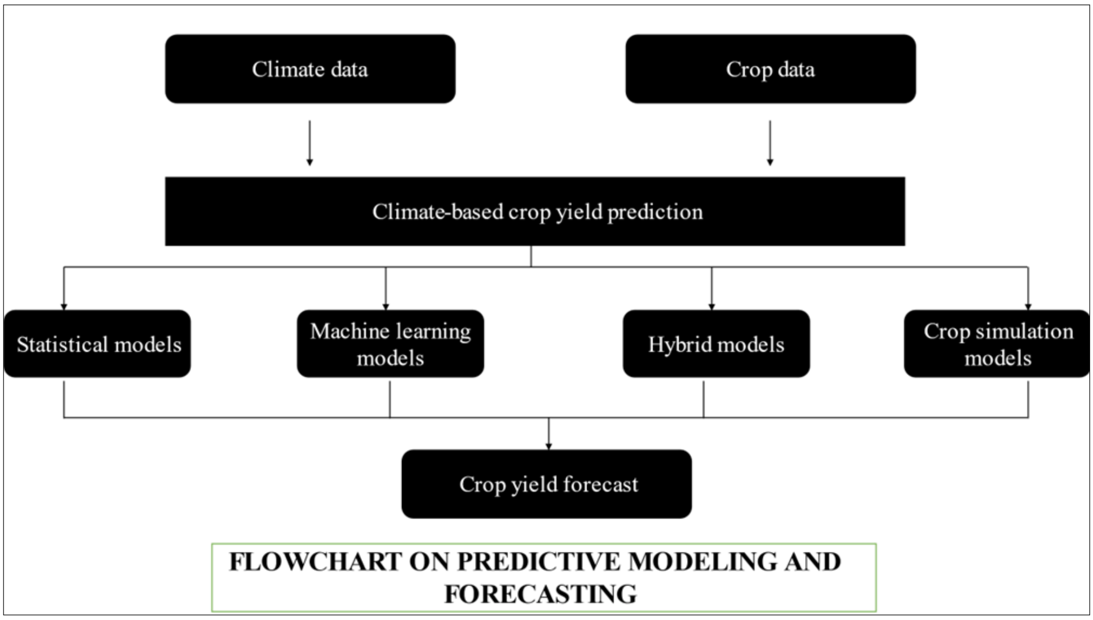

Fig. 3. Flowchart on Climate-based crop yield prediction models.

Table 2. Predictive modeling and forecasting in climate-based crop yield prediction

Model type	Approach/Tool	Applications	Advantages	References
Statistical models	-Multiple linear regression (MLR) - ARIMA	Forecasting cereal yields (wheat, maize, rice) using ENSO, NAO indices	Simple to implement; effective for historical data trends	(41)
Machine learning models	- Random forests - Support vector machines - Deep learning	Capturing nonlinear crop-climate interactions; seasonal crop forecasts	High accuracy; handles complex data; adaptable to diverse regions	(80)
Dynamic crop simulation models	- DSSAT - APSIM - WOFOST	Simulating crop responses to climate variables; used with ENSO/IOD forecasts	Process-based; detailed physiological modeling; suitable for scenario testing	(81, 99)
Ensemble models	- Multiple crop and climate models combined	Regional and national yield forecasts with probability outputs	Incorporates uncertainty; suitable for insurance and early warning systems	(82)
Hybrid models	- Climate indices, remote sensing and socioeconomic data	Food security planning; FAO/WFP use; drought and flood risk monitoring	Combines spatial, biophysical and social data; real-time decision support	(8)
Emerging tools	- AI-driven platforms - Cloud-based DSS tools	Localized, real-time forecasts; mobile advisory services to farmers	Fast processing; user-friendly interfaces; scalable to smallholder contexts	(83)

applications and advantages. Statistical models, such as Multiple Linear Regression (MLR) and ARIMA, have been widely used to forecast yields of major cereals like wheat, maize and rice by incorporating climate indices such as ENSO and NAO. These models are simple to implement and are particularly effective when applied to historical trend analysis (41). Machine learning models, including Random Forests, Support Vector Machines and Deep Learning algorithms, offer the ability to capture complex, nonlinear relationships between climate variables and crop yields. These tools have demonstrated high accuracy in seasonal forecasting and can be effectively adapted to diverse agro-climatic zones (80). Dynamic crop simulation models such as DSSAT, APSIM and WOFOST simulate crop growth processes under varying climate conditions. These models are process-based and allow for detailed physiological modeling, making them suitable for scenario testing using forecasts from climate phenomena like ENSO and IOD (7, 81).

Ensemble models, which combine multiple crop and climate models, are used for regional and national yield forecasting. Their strength lies in incorporating uncertainty and providing probabilistic outputs, making them valuable for applications in crop insurance schemes and early warning systems (82). Hybrid models integrate climate indices with remote sensing data and socio-economic variables. These models are especially useful for food security planning and are employed by organizations like FAO and WFP to monitor drought and flood risks. They provide robust decision-support by combining spatial, biophysical and social datasets (8). Lastly, emerging tools such as AI-driven platforms and cloud-based decision support systems (DSS) enable real-time, localized forecasting. These platforms are increasingly used for mobile advisory services to farmers, offering fast data processing, user-friendly interfaces and scalability for smallholder agricultural systems (83).

The Table 2 provides an overview of these forecasting methods, their practical applications in agriculture, key benefits and supporting literature (Fig. 4).

Adaptation and mitigation strategies

» Climate-smart agriculture (CSA) enhances resilience and mitigation by improving soil health, increasing water-use efficiency and promoting carbon sequestration through practices like crop rotation, agroforestry and conservation tillage (84).

» Soil management practices such as cover cropping, no-till farming and residue mulching can improve soil organic carbon and contribute to reducing global agricultural GHG emissions by 5 –15 % (85).

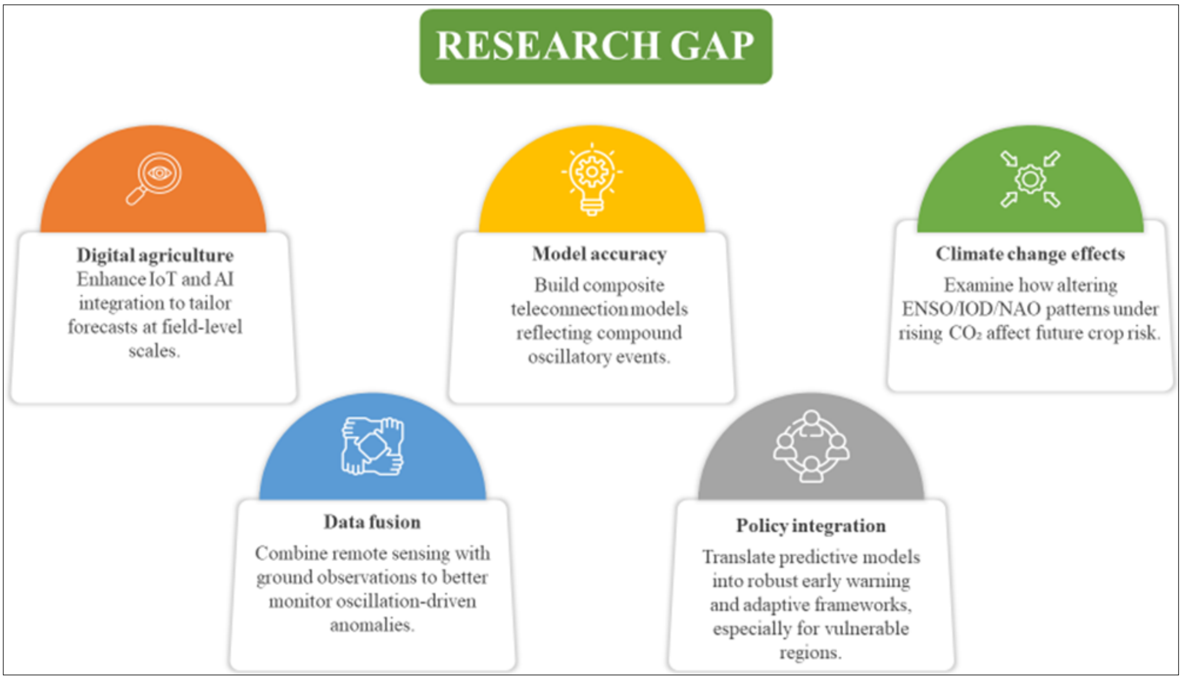

Fig. 4. Research gap.

» Season-specific nitrogen management strategies, including split nitrogen application during key growth stages, reduce both yield variability and nitrogen leaching under El Niño and La Niña conditions. For example, in northern India, split nitrogen application in rice and wheat systems has been shown to improve nitrogen use efficiency and stabilize yields during monsoon variability associated with ENSO phases (86).

» Water-saving irrigation methods like drip and sprinkler systems enhance irrigation efficiency, reduce groundwater depletion and offer long-term resilience to semi-arid farming systems (87).

» Agroforestry and Ecosystem-based Adaptation (EbA) techniques improve soil moisture, reduce erosion and support biodiversity, making them effective tools for managing erratic rainfall and climate stress (88).

» Traditional adaptation practices, including crop diversification, short-season varieties and moisture conservation, are widely used by smallholders in Africa to cope with increasing climate variability (89).

» Climate information services, including ENSO-based seasonal forecasts, support anticipatory actions such as altering planting schedules and preparing for extreme weather events (90).

» Digital technologies like AI-powered remote sensing tools help track real-time soil moisture and weather, enabling farmers to make timely and informed adaptation decisions. Platforms such as the IBM Watson Decision Platform for Agriculture, CropIn's SmartFarm and Microsoft AI for Earth provide farmers with field-specific forecasts, crop health insights and actionable advisories tailored to climate variability (91).

» Policy support programs, such as India's Climate Resilient Agriculture initiative, integrate crop insurance, drought-resilient varieties and community resource banks to enhance local adaptation capacity (92).

» Long-term adaptive pathways, including land-use diversification and agroecological transitions, offer synergies between mitigation, biodiversity conservation and yield stability (93).

Future research directions

✓ Incorporating detailed climate oscillation signals (e.g., ENSO, IOD) into crop models enhances the predictability of yields under changing climate regimes (74).

✓ Regional downscaling and sub-seasonal forecasts tailored to farmers' needs are crucial for operational climate services (94).

✓ AI and machine learning enhance precision agriculture through real-time weather and crop condition analysis, improving farm-level decisions (95).

✓ Indigenous adaptation strategies provide locally tested solutions to climate risks and should be part of formal adaptation planning (96).

✓ Weather-indexed insurance and early warning-linked credit systems are key tools to protect smallholder livelihoods against climate variability (97).

✓ Coordinated governance across climate, agriculture and disaster risk sectors enhances resilience-building and mainstreams climate information (98).

Conclusion

Agriculture is increasingly vulnerable to climate variability, making it crucial to understand the influence of large-scale oscillations like ENSO, IOD and NAO. These global phenomena have significant local impacts, affecting crop yields and the resilience of farming communities. This review highlights the value of integrating climate oscillation signals into agricultural planning through tools like AI-driven forecasting and dynamic crop models. However, the effectiveness of these tools depends on robust delivery systems and stakeholder trust, particularly in resource-limited regions. To enhance impact, seasonal climate forecasts should be systematically integrated into national agrometeorological advisory bulletins, enabling farmers to make timely decisions on sowing, irrigation and input use. Investment in climate services infrastructure, especially localized forecast calibration and last-mile delivery via mobile apps or community platforms, is critical. Policymakers should also promote interdisciplinary research that links climate science, agronomy and socioeconomics to develop adaptive cropping systems. Finally, capacity-building for extension personnel and the inclusion of indigenous knowledge systems will ensure that climate information is both context-sensitive and actionable, thereby strengthening agricultural resilience and long-term food security.

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Authors' contributions

DS was responsible for conceptualization, literature review, methodology and writing-original draft preparation. NKS provided supervision, performed manuscript review and editing, made critical revisions and gave final approval of the manuscript. All authors read and approved the final version of the manuscript.

Compliance with ethical standards

Conflict of interest: The authors declare that there is no conflict of interest.

Ethical issues: None

Declaration of generative AI and AI-assisted technologies in the writing process

AI tools, including Quill Bot, were used solely for language editing and formatting purposes. All scientific content, data interpretation and conclusions were developed and validated by the authors in accordance with journal guidelines.

References

1. Ray DK, Gerber JS, MacDonald GK, West PC. Climate variation explains a third of global crop yield variability. Nat Commun. 2015;6(1):5989. https://doi.org/10.1038/ncomms6989
2. Coumou D, Rahmstorf S. A decade of weather extremes. Nat Clim Change. 2012;2(7):491-6. https://doi.org/10.1038/nclimate1452
3. Porter J, Xie L, Challinor A, Cochrane K, Howden S, Iqbal M, et al. Food security and food production systems climate change 2014: impacts, adaptation and vulnerability. Part a: global and sectoral aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge (UK): Cambridge University Press; 2014. p. 485-533.
4. Saji N, Goswami BN, Vinayachandran P, Yamagata T. A dipole mode in the tropical Indian Ocean. Nature. 1999;401(6751):360-3. https://doi.org/10.1038/43854
5. Ummenhofer CC, England MH, McIntosh PC, Meyers GA, Pook MJ, Risbey JS, et al. What causes southeast Australia's worst droughts? Geophys Res Lett. 2009;36(4). https://doi.org/10.1029/2008GL036801
6. Cai W, Borlace S, Lengaigne M, Van Rensch P, Collins M, Vecchi G, et al. Increasing frequency of extreme El Niño events due to greenhouse warming. Nat Clim Change. 2014;4(2):111-6. https://doi.org/10.1038/nclimate2100
7. Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt LA, et al. The DSSAT cropping system model. Eur J Agron. 2003;18(3-4):235-65. https://doi.org/10.1016/S1161-0301(02)00107-7
8. Lobell DB, Burke MB. On the use of statistical models to predict crop yield responses to climate change. Agric For Meteorol. 2010;150(11):1443-52. https://doi.org/10.1016/j.agrformet.2010.07.008
9. Meehl GA, Arblaster JM, Tebaldi C. Understanding future patterns of increased precipitation intensity in climate model simulations. Geophys Res Lett. 2005;32(18). https://doi.org/10.1029/2005GL023680
10. Tesfamariam BG, Gessesse B, Melgani F. Characterizing the spatiotemporal distribution of meteorological drought as a response to climate variability: The case of rift valley lakes basin of Ethiopia. Weather Clim Extremes. 2019;26:100237. https://doi.org/10.1016/j.wace.2019.100237
11. Nicholson SE. A detailed look at the recent drought situation in the Greater Horn of Africa. J Arid Environ. 2014;103:71-9. https://doi.org/10.1016/j.jaridenv.2013.12.003
12. Tall A, Coulibaly JY, Diop M. Do climate services make a difference? A review of evaluation methodologies and practices to assess the value of climate information services for farmers: Implications for Africa. Clim Serv. 2018;11:1-12. https://doi.org/10.1016/j.cliser.2018.06.001
13. Vermeulen SJ, Aggarwal PK, Ainslie A, Angelone C, Campbell BM, Challinor AJ, et al. Options for support to agriculture and food security under climate change. Environ Sci Policy. 2012;15(1):136-44. https://doi.org/10.1016/j.envsci.2011.09.003
14. Waha K, Müller C, Bondeau A, Dietrich JP, Kurukulasuriya P, Heinke J, et al. Adaptation to climate change through the choice of cropping system and sowing date in sub-Saharan Africa. Glob Environ Change. 2013;23(1):130-43. https://doi.org/10.1016/j.gloenvcha.2012.11.001
15. Challinor A, Wheeler T, Garforth C, Craufurd P, Kassam A. Assessing the vulnerability of food crop systems in Africa to climate change. Clim Change. 2007;83(3):381-99. https://doi.org/10.1007/s10584-007-9249-0
16. Hansen JW, Challinor A, Ines A, Wheeler T, Moron V. Translating climate forecasts into agricultural terms: advances and challenges. Clim Res. 2006;33:27-41. https://doi.org/10.3354/cr033027
17. McCabe MF, Rodell M, Alsdorf DE, Miralles DG, Uijlenhoet R, Wagner W, et al. The future of Earth observation in hydrology. Hydrol Earth Syst Sci. 2017;21(7):3879-914. https://doi.org/10.5194/hess-21-3879-2017
18. Zhang G, Wu Y, Zhao W, Zhang J. Radar-based multipoint displacement measurements of a 1200-m-long suspension bridge. ISPRS J Photogramm Remote Sens. 2020;167:71-84. https://doi.org/10.1016/j.isprsjprs.2020.06.017
19. Roncoli C, Jost C, Kirshen P, Sanon M, Ingram KT, Woodin M, et al. From accessing to assessing forecasts: an end-to-end study of participatory climate forecast dissemination in Burkina Faso (West Africa). Clim Change. 2009;92:433-60. https://doi.org/10.1007/s10584-008-9445-6
20. Zougmoré RB, Partey ST, Totin E, Ouédraogo M, Thornton P, Karbo N, et al. Science-policy interfaces for sustainable climate-smart agriculture uptake: lessons learnt from national science-policy dialogue platforms in West Africa. Int J Agric Sustain. 2019;17(5):367-82. https://doi.org/10.1080/14735903.2019.1670934
21. Washington R, Harrison M, Conway D, Black E, Challinor A, Grimes D, et al. African climate change: taking the shorter route. Bull Am Meteorol Soc. 2006;87(10):1355-66. https://doi.org/10.1175/BAMS-87-10-1355
22. Singh C, Tebboth M, Spear D, Ansah P, Mensah A. Exploring methodological approaches to assess climate change

vulnerability and adaptation: reflections from using life history approaches. Reg Environ Change. 2019;19(8):2667-82. https://doi.org/10.1007/s10113-019-01562-z

23. Achli S, Epule TE, Dhiba D, Salih W, Chehbouni A. Vulnerability of maize, barley and wheat yields to growing season temperature and socioeconomic indicators in Morocco. J Water Clim Change. 2024;15(4):1588-611. https://doi.org/10.2166/wcc.2024.498

24. Kristjanson P, Neufeldt H, Gassner A, Mango J, Kyazze FB, Desta S, et al. Are food insecure smallholder households making changes in their farming practices? Evidence from East Africa. Food Sec. 2012;4(3):381-97. https://doi.org/10.1007/s12571-012-0194-z

25. Roncoli C, Ingram K, Kirshen P. Reading the rains: Local knowledge and rainfall forecasting in Burkina Faso. Soc Nat Resour. 2002;15(5):409-27. https://doi.org/10.1080/08941920252866774

26. Harvey CA, Rakotobe ZL, Rao NS, Dave R, Razafimahatratra H, Rabarijohn RH, et al. Extreme vulnerability of smallholder farmers to agricultural risks and climate change in Madagascar. Philos Trans R Soc B Biol Sci. 2014;369(1639):20130089. https://doi.org/10.1098/rstb.2013.0089

27. Islam N, Winkel J. Climate change and social inequality. New York (NY): United Nations, Department of Economic and Social Affairs (DESA); 2017.

28. Fader M, Gerten D, Krause M, Lucht W, Cramer W. Spatial decoupling of agricultural production and consumption: quantifying dependences of countries on food imports due to domestic land and water constraints. Environ Res Lett. 2013;8(1):014046. https://doi.org/10.1088/1748-9326/8/1/014046

29. Nelson GC, Valin H, Sands RD, Havlík P, Ahammad H, Deryng D, et al. Climate change effects on agriculture: Economic responses to biophysical shocks. Proc Natl Acad Sci U S A. 2014;111(9):3274-9. https://doi.org/10.1073/pnas.1222465110

30. Tziperman E, Zebiak SE, Cane MA. Mechanisms of seasonal-ENSO interaction. J Atmos Sci. 1997;54(1):61-71. https://doi.org/10.1175/1520-0469(1997)054%3C0061:MOSEI%3E2.0.CO;2

31. Akhmet M, Fen MO, Alejaily EM. The Effects of El Niño on the global weather and climate. arXiv preprint arXiv:180100891. 2018.

32. Ineson S, Scaife A. The role of the stratosphere in the European climate response to El Niño. Nat Geosci. 2009;2(1):32-6. https://doi.org/10.1038/ngeo381

33. Butler AH, Polvani LM, Deser C. Separating the stratospheric and tropospheric pathways of El Niño-Southern Oscillation teleconnections. Environ Res Lett. 2014;9(2):024014. https://doi.org/10.1088/1748-9326/9/2/024014

34. Kämpf J. Do coastal or equatorial wind anomalies drive the Indian Ocean Dipole? J Mar Syst. 2024;246:104016. https://doi.org/10.1016/j.jmarsys.2024.104016

35. Ratna SB, Cherchi A, Osborn TJ, Joshi M, Uppara U. The extreme positive indian ocean dipole of 2019 and associated indian summer monsoon rainfall response. Geophys Res Lett. 2021;48(2):e2020GL091497. https://doi.org/10.1029/2020GL091497

36. Ropelewski CF, Halpert MS. Global and regional scale precipitation patterns associated with the El Niño/Southern Oscillation. Mon Weather Rev. 1987;115(8):1606-26. https://doi.org/10.1175/1520-0493(1987)115%3C1606:GARSPP%3E2.0.CO;2

37. Hurrell JW. Decadal trends in the North Atlantic oscillation: Regional temperatures and precipitation. Science. 1995;269(5224):676-9. https://doi.org/10.1126/science.269.5224.676

38. Hurrell JW, Deser C. North Atlantic climate variability: The role of the North Atlantic Oscillation. J Mar Syst. 2010;79(3):231-44. https://doi.org/10.1016/j.jmarsys.2009.11.002

39. Walker G, Bliss E. Memoirs of the royal meteorological society. World weather V. 1932;4:53-84.

40. Iglesias A, Garrote L, Quiroga S, Moneo M. A regional comparison of the effects of climate change on agricultural crops in Europe. Clim Change. 2012;112:29-46.

41. Krishna Kumar K, Kumar RK, Ashrit R, Deshpande N, Hansen JW. Climate impacts on Indian agriculture. Int J Climatol. 2004;24(11):1375-93. https://doi.org/10.1002/joc.1081

42. Kumar KK, Rajagopalan B, Cane MA. On the weakening relationship between the Indian Monsoon and ENSO. Science. 1999;284(5423):2156-9. https://doi.org/10.1126/science.284.5423.2156

43. Cai W, Cowan T, Sullivan A. Recent unprecedented skewness towards positive Indian Ocean Dipole occurrences and its impact on Australian rainfall. Geophys Res Lett. 2009;36(11). https://doi.org/10.1029/2009GL037604

44. Funk C, Dettinger MD, Michaelsen JC, Verdin JP, Brown ME, Barlow M, et al. Warming of the Indian Ocean threatens eastern and southern African food security but could be mitigated by agricultural development. Proc Natl Acad Sci U S A. 2008;105(32):11081-6. https://doi.org/10.1073/pnas.0708196105

45. Trnka M, Feng S, Semenov MA, Olesen JE, Kersebaum KC, Rötter RP, et al. Mitigation efforts will not fully alleviate the increase in water scarcity occurrence probability in wheat-producing areas. Sci Adv. 2019;5(9):eaau2406. https://doi.org/10.1126/sciadv.aau2406

46. Handler P, Andsager K. Volcanic aerosols, El Niño and the Southern Oscillation. Int J Climatol. 1990;10(4):413-24. https://doi.org/10.1002/joc.3370100409

47. Baethgen WE. Vulnerability of the agricultural sector of Latin America to climate change. Clim Res. 1997;9(1-2):1-7. https://doi.org/10.3354/cr009001

48. Santer BD, Wigley T, Barnett TP, Anyamba E, Bloomfield P, Cook E, et al. Detection of climate change and attribution of causes. In: Climate Change 1995: The Science of Climate Change: Contribution of Working Group I to the Second Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge (UK): Cambridge University Press; 1996. p. 411-39.

49. Monteleone B, Borzí I, Bonaccorso B, Martina M. Quantifying crop vulnerability to weather-related extreme events and climate change through vulnerability curves. Nat Hazards. 2023;116(3):2761-96. https://doi.org/10.1007/s11069-022-05791-0

50. Wahid A, Gelani S, Ashraf M, Foolad MR. Heat tolerance in plants: an overview. Environ Exp Bot. 2007;61(3):199-223. https://doi.org/10.1016/j.envexpbot.2007.05.011

51. Jagadish SK, Craufurd PQ, Wheeler T. High temperature stress and spikelet fertility in rice (*Oryza sativa* L.). J Exp Bot. 2007;58(7):1627-35. https://doi.org/10.1093/jxb/erm003

52. Flexas J, Medrano H. Drought-inhibition of photosynthesis in C3 plants: stomatal and non-stomatal limitations revisited. Ann Bot. 2002;89(2):183-9. https://doi.org/10.1093/aob/mcf027

53. Tardieu F, Davies W. Integration of hydraulic and chemical signalling in the control of stomatal conductance and water status of droughted plants. Plant Cell Environ. 1993;16(4):341-9. https://doi.org/10.1111/j.1365-3040.1993.tb00880.x

54. Ashraf M, Foolad MR. Roles of glycine betaine and proline in improving plant abiotic stress resistance. Environ Exp Bot. 2007;59(2):206-16. https://doi.org/10.1016/j.envexpbot.2005.12.006

55. Mittler R. Oxidative stress, antioxidants and stress tolerance. Trends Plant Sci. 2002;7(9):405-10. https://doi.org/10.1016/S1360-1385(02)02312-9

56. Hsiao J, Swann AL, Kim S-H. Maize yield under a changing climate: The hidden role of vapor pressure deficit. Agric For Meteorol. 2019;279:107692. https://doi.org/10.1016/j.agrformet.2019.107692

57. Senthilnathan S, Benson D, Prasanna V, Mallick T, Thiyagarajan A, Ramasamy M, et al. Impact of climate variability on Maize yield under different climate change scenarios in Southern India: A Panel Data Approach. Earth. 2025;6(1):16. https://doi.org/10.3390/earth6010016

58. Su P, Li S, Wang Ja, Liu F. Vulnerability assessment of Maize yield affected by precipitation fluctuations: A Northeastern United States case study. Land. 2021;10(11):1190. https://doi.org/10.3390/land10111190

59. Shuai J, Zhang Z, Tao F, Shi P. How ENSO affects maize yields in China: understanding the impact mechanisms using a process-based crop model. Int J Climatol. 2016;36(1). https://doi.org/10.1002/joc.4360

60. Epule TE, Chehbouni A, Dhiba D, Etongo D, Driouech F, Brouziyne Y, et al. Vulnerability of Maize, millet and rice yields to growing season precipitation and socio-economic proxies in Cameroon. PLoS One. 2021;16(6):e0252335. https://doi.org/10.1371/journal.pone.0252335

61. Sazib N, Mladenova lE, Bolten JD. Assessing the impact of ENSO on agriculture over Africa using Earth Observation Data. Front Sustain Food Syst. 2020;4:509914. https://doi.org/10.3389/fsufs.2020.509914

62. Khedwal RS, Chaudhary A, Sindhu VK, Yadav DB, Kumar N, Chhokar RS, et al. Challenges and technological interventions in rice-wheat system for resilient food-water-energy-environment nexus in North-western Indo-Gangetic Plains: A review. Cereal Res Commun. 2023:1-23. https://doi.org/10.1007/s42976-023-00355-9

63. Le T, Bae DH. Causal impacts of El Niño-Southern Oscillation on global soil moisture over the period 2015-2100. Earths Future. 2022;10(3):e2021EF002522. https://doi.org/10.1029/2021EF002522

64. Cai W, van Rensch P, Cowan T, Hendon HH. Teleconnection pathways of ENSO and the IOD and the mechanisms for impacts on Australian rainfall. J Clim. 2011;24(15):3910-23. https://doi.org/10.1175/2011JCLI4129.1

65. Wu C, Yeh PJF, Wu H, Hu BX, Huang G. Global analysis of the role of terrestrial water storage in the evapotranspiration estimated from the Budyko framework at annual to monthly time scales. J Hydrometeorol. 2019;20(10):2003-21. https://doi.org/10.1175/JHM-D-19-0065.1

66. Yin H, Wu Z, Fowler HJ, Blenkinsop S, He H, Li Y. The combined impacts of ENSO and IOD on global seasonal droughts. Atmosphere. 2022;13(10):1673. https://doi.org/10.3390/atmos13101673

67. Yan J, Zhang W, Hu S, Jiang F. Different ENSO impacts on eastern China precipitation patterns in early and late winter associated with seasonally-varying kuroshio anticyclonic anomalies. Adv Atmos Sci. 2024;41(9):1691-703. https://doi.org/10.1007/s00376-023-3196-1

68. Niu J, Chen J, Sivakumar B. Teleconnection analysis of runoff and soil moisture over the Pearl River basin in southern China. Hydrol Earth Syst Sci. 2014;18(4):1475-92. https://doi.org/10.5194/hess-18-1475-2014

69. Chauhan AS, Rani A, Dahiya P, Maurya RKS, Danodia A. Understanding the influence of teleconnections on Indian summer monsoon rainfall and agricultural productivity: a case study of Haryana, India (1980-2023). J Water Clim Change. 2024;15(12):5793-816. https://doi.org/10.2166/wcc.2024.311

70. Makarieva AM, Nefiodov AV, Nobre AD, Baudena M, Bardi U, Sheil D, et al. The role of ecosystem transpiration in creating alternate moisture regimes by influencing atmospheric moisture convergence. Glob Change Biol. 2023;29(9):2536-56. https://doi.org/10.1111/gcb.16644

71. Trigo R, Osborn T, Corte-Real J. The North Atlantic oscillation influence on Europe: climate impacts and associated physical mechanisms. Clim Res. 2002;20:9-17. https://doi.org/10.3354/cr020009

72. Challinor AJ, Watson J, Lobell DB, Howden SM, Smith D, Chhetri N. A meta-analysis of crop yield under climate change and adaptation. Nat Clim Change. 2014;4(4):287-91. https://doi.org/10.1038/nclimate2153

73. Holzworth DP, Huth NI, deVoil PG, Zurcher EJ, Herrmann NI, McLean G, et al. APSIM-evolution towards a new generation of agricultural systems simulation. Environ Model Softw. 2014;62:327-50. https://doi.org/10.1016/j.envsoft.2014.07.009

74. Lobell DB, Asseng S. Comparing estimates of climate change impacts from process-based and statistical crop models. Environ Res Lett. 2017;12(1):015001. https://doi.org/10.1088/1748-9326/aa518a

75. Martre P, Wallach D, Asseng S, Ewert F, Jones JW, Rötter RP, et al. Multimodel ensembles of wheat growth: many models are better than one. Glob Change Biol. 2015;21(2):911-25. https://doi.org/10.1111/gcb.12768

76. Lobell DB. Climate change adaptation in crop production: Beware of illusions. Glob Food Sec. 2014;3(2):72-6. https://doi.org/10.1016/j.gfs.2014.05.002

77. Challinor A, Slingo J, Wheeler T, Craufurd P, Grimes D. Toward a combined seasonal weather and crop productivity forecasting system: determination of the working spatial scale. J Appl Meteorol. 2003;42(2):175-92. https://doi.org/10.1175/1520-0450(2003)042%3C0175:TACSWA%3E2.0.CO;2

78. Kuwata K, Shibasaki R. Estimating corn yield in the united states with modis evi and machine learning methods. ISPRS Ann Photogramm Remote Sens Spatial Inf Sci. 2016;3:131-6. https://doi.org/10.5194/isprs-annals-III-8-131-2016

79. Hochman Z, Holzworth D, Hunt JR. Potential to improve on-farm wheat yield and WUE in Australia. Crop Pasture Sci. 2009;60(8):708-16. https://doi.org/10.1071/CP09064

80. Asseng S, Ewert F, Rosenzweig C, Jones JW, Hatfield JL, Ruane AC, et al. Uncertainty in simulating wheat yields under climate change. Nat Clim Change. 2013;3(9):827-32. https://doi.org/10.1038/nclimate1916

81. Thornton PK, Ericksen PJ, Herrero M, Challinor AJ. Climate variability and vulnerability to climate change: a review. Glob Change Biol. 2014;20(11):3313-28. https://doi.org/10.1111/gcb.12581

82. Goli I, Kriaučiūnienė Z, Zhang R, Bijani M, Koohi PK, Rostamkalaei SA, et al. Contributions of climate smart agriculture toward climate change adaptation and food security: The case of Mazandaran Province, Iran. Trends Food Sci Technol. 2024:104653. https://doi.org/10.1016/j.tifs.2024.104653

83. Ellis E, Paustian K. Importance of on-farm research for validating process-based models of climate-smart agriculture. Carbon Balance Manag. 2024;19(1):16. https://doi.org/10.1186/s13021-024-00260-6

84. Zhang X, Davidson EA, Mauzerall DL, Searchinger TD, Dumas P, Shen Y. Managing nitrogen for sustainable development. Nature. 2015;528(7580):51-9. https://doi.org/10.1038/nature15743

85. Hunsaker DJ, Bronson KF. FAO56 crop and water stress coefficients for cotton using subsurface drip irrigation in an arid US climate. Agric Water Manag. 2021;252:106881. https://doi.org/10.1016/j.agwat.2021.106881

86. Verchot LV, Van Noordwijk M, Kandji S, Tomich T, Ong C, Albrecht A, et al. Climate change: linking adaptation and mitigation through agroforestry. Mitig Adapt Strateg Glob Change. 2007;12:901-18. https://doi.org/10.1007/s11027-007-9105-6

87. Incoom ABM, Adjei KA, Odai SN, Siabi EK, Donkor P, Frimpong K. Adaptation strategies by smallholder farmers to climate change and variability: The case of the savannah zone of Ghana. Sustain Futures. 2025;9:100543. https://doi.org/10.1016/j.sftr.2025.100543

88. Maher N, Wills RCJ, DiNezio P, Klavans J, Milinski S, Sanchez SC, et al. The future of the El Niño-Southern oscillation: using large ensembles to illuminate time-varying responses and inter-model differences. Earth Syst Dyn. 2023;14(2):413-31. https://doi.org/10.5194/esd-14-413-2023

89. Sirmacek B, Vinuesa R. Remote sensing and AI for building climate adaptation applications. Results Eng. 2022;15:100524. https://doi.org/10.1016/j.rineng.2022.100524

90. Baraj B, Mishra M, Sudarsan D, da Silva RM, Santos CAG. Climate change and resilience, adaptation and sustainability of agriculture in India: A bibliometric review. Heliyon. 2024. https://doi.org/10.1016/j.heliyon.2024.e29586

91. Das A, Rewari S, Kanaujia BK, Deswal S, Gupta R. Physics based numerical model of a nanoscale dielectric modulated step graded germanium source biotube FET sensor: modelling and simulation. Phys Scr. 2023;98(11):115013. https://doi.org/10.1088/1402-4896/acf4c9

92. Hansen JW, Mason SJ, Sun L, Tall A. Review of seasonal climate forecasting for agriculture in sub-Saharan Africa. Exp Agric. 2011;47(2):205-40. https://doi.org/10.1017/S0014479710000876

93. Van Klompenburg T, Kassahun A, Catal C. Crop yield prediction using machine learning: A systematic literature review. Comput Electron Agric. 2020;177:105709. https://doi.org/10.1016/j.compag.2020.105709

94. Nyong A, Adesina F, Osman Elasha B. The value of indigenous knowledge in climate change mitigation and adaptation strategies in the African Sahel. Mitig Adapt Strateg Glob Change. 2007;12:787-97. https://doi.org/10.1007/s11027-007-9099-0

95. Greatrex H, Hansen J, Garvin S, Diro R, Le Guen M, Blakeley S, et al. Scaling up index insurance for smallholder farmers: Recent evidence and insights. Greatrex H, Hansen J, Garvin S, Diro R, Blakeley S, Le Guen M, et al. Scaling up index insurance for smallholder farmers: recent evidence and insights [Internet]. CCAFS Report No. 14. Copenhagen (Denmark): CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS); 2015 [cited 2025 Nov 30]. https://hdl.handle.net/10568/53101

96. Antwi-Agyei P, Dougill AJ, Agyekum TP, Stringer LC. Alignment between nationally determined contributions and the sustainable development goals for West Africa. Clim Policy. 2018;18(10):1296-312. https://doi.org/10.1080/14693062.2018.1431199

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