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Crop simulation-based assessment of yield gaps and water productivity for improving blackgram (*Vigna mungo* L.) production across diverse ecologies of India

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Blackgram (*Vigna mungo* L.), a nutritionally and ecologically important pulse crop in India, remains constrained by climatic stress, moisture limitations, and suboptimal agronomic management. To identify pathways for sustainable intensification, the APSIM model was employed to simulate potential yield (Yp), quantify yield gaps, and assess water productivity across twenty major blackgram-growing districts of India during 2003-2023. Simulations integrated long-term weather data, soil profiles, region-specific management practices, and cultivar-specific genetic coefficients, while water productivity was evaluated using physical (PWP), irrigation (IWP), and economic (EWP) indices. Observed yields (280–1040 kg ha^{-1}) were consistently lower than simulated potential yields (840–1176 kg ha^{-1}), revealing yield gaps ranging from 5 to 67%, with an average gap of about 515 kg ha^{-1}. Central Zone districts exhibited the widest gaps, whereas rice-fallow systems in the South Zone showed relatively higher productivity and economic water returns. Model performance was robust, with high accuracy during calibration and validation (R^2 and NSE ≈ 0.97-0.99; RMSE ≤20%; NMSE<0.05). District-level carbon budgeting revealed blackgram to be a consistent net carbon sink, with carbon efficiency ranging from 7.05-9.69 and a mean CSI of 7.21. Principal Component Analysis identified nutrient-water coupling (N, P, and irrigation), soil organic carbon, and yield components as dominant drivers of yield variability, while correlation-density matrix analysis highlighted strong interdependence among reproductive traits and trade-offs with crop geometry. Bridging yield and water productivity gaps through climate-resilient varieties, optimized crop geometry, precision irrigation, and targeted policy support can substantially enhance blackgram productivity and resource-use efficiency.

KEYWORDS
APSIM, blackgram, carbon budget, principal component analysis, water productivity, yield gap

1 Introduction

Blackgram (*Vigna mungo* L.), commonly known as urd or urad, is an indigenous legume of India and a major component of South Asian cropping systems. Blackgram grains are nutritionally rich, containing approximately 24% protein and 59.6% carbohydrates, along with 100g of grains contains around 154 mg calcium, 385 mg phosphorus, and 9.1 mg iron (Venkidasamy et al., 2019). The protein quality of blackgram is considered high due to its favorable essential amino acid composition, making it an important dietary protein source, particularly for vegetarian populations (Kamani and Meera, 2021). Beyond its nutritional value, blackgram is endowed with biological nitrogen fixation (BNF), thereby helping in the maintenance of soil fertility and nutrient availability for subsequent crops. Consequently, blackgram plays a critical role in rice-fallow systems and cereal-based rotations, which are facing a paradox of meeting the food demand of the rapidly growing global population, expected to reach around 10 billion by 2050 (FAO, 2017) while protecting the environment and reducing resource footprint (Chakraborti et al., 2019; Belete and Yadete, 2023; Elouattassi et al., 2023). Owing to their high nutritional value alongside the ecological services, pulses such as blackgram play a crucial role in sustainable intensification and diversification while alleviating protein-energy malnutrition, contributing directly to the United Nations Sustainable Development Goal 2 of Zero Hunger (Suri, 2024).

Moreover, blackgram cultivation is a vital component of India's pulse economy and food security contributing more than 70% to global blackgram production, reflecting its global dominance (Kavisri and Sundararaj, 2025). The crop occupies nearly 29% of the total pulse area in the country and contributes approximately 10.25% of total pulse production. During 2023-24, blackgram production was estimated at about 2 million tonnes from nearly 4 million hectares (ANGRAU, 2024). However, national productivity of blackgram remains relatively low, with average yields stagnating at around 542–662 kg ha^{-1} (Swaminathan et al., 2023), substantially lower than yields attainable under research and improved management conditions. Approximately 80% of blackgram cultivation occurs during the *kharif* season, while the remaining 20% is grown during the *rabi* season, particularly in rice-fallow systems using short-duration varieties (ANGRAU, 2024). Major production regions include Maharashtra, Madhya Pradesh, and the rice-fallow belts of Andhra Pradesh and Tamil Nadu.

However, productivity of blackgram is constrained by a complex interaction of abiotic, biotic, and management-related stresses. The crop is particularly vulnerable to terminal heat stress and soil moisture deficits during the spring-summer season, which disrupt physiological processes, reduce photosynthetic efficiency, and result in poor seed set, especially in the Gangetic plains of Eastern India (Banerjee et al., 2021b). Biotic stresses further exacerbate yield losses, with Mungbean Yellow Mosaic Virus (MYMV) capable of causing yield reductions exceeding 50% in Vigna species. Insect pests such as pod borers (*Maruca vitrata* and *Helicoverpa armigera*) also pose serious challenges, leading to significant quantitative and qualitative yield losses (Sankaran et al., 2024).

Management-related constraints substantially widen the observed yield gap in blackgram cultivation. Studies on pulse production systems in India indicate that the yield gap between potential yields and farmers' yields ranges from 30-50%, highlighting significant scope for productivity enhancement through improved agronomic and management practices (Reddy, 2009). Farmers frequently cite inadequate weed management, limited availability of improved production technologies suitable for rice-fallow systems, and poor access to quality seed and technical advisory services as major constraints (Kumar et al., 2020). To systematically diagnose and address these productivity shortfalls, it is essential to quantify the "yield gap" (Yg) between the potential yield and realizable yield in farmers field (Van Ittersum et al., 2013). Yield potential (Yp) is the ceiling yield achievable by a cultivar under stress-free conditions with optimal management, primarily governed by climate and soil properties. Quantification of yield gaps at appropriate spatial and temporal scales is crucial for prioritizing national agricultural research and development investments to ensure sustainable intensification and food security (Yuan et al., 2021).

Further, pronounced regional variability in water availability across India, making productivity gains as important as improvements in water-use efficiency, that can be assessed through the concept of water productivity (WP) (Van Halsema and Vincent, 2012; Chakraborti et al., 2019). Physical Water Productivity (PWP), Irrigation Water Productivity (IWP), and Economic Water Productivity (EWP) are several indicators to assess water productivity, which enables evaluation of both biophysical efficiency and economic viability. This is particularly relevant for blackgram, which is predominantly cultivated under rainfed or residual moisture conditions and is highly sensitive to short-term water stress (Banerjee et al., 2021). Blackgram generally requires about 350–500 mm of water for successful cultivation.Since it is predominantly grown under rainfed conditions during the *kharif* season, the crop often experiences moisture stress during reproductive stages and may occasionally face waterlogging under excessive rainfall conditions (Ahlawat and Shivakumar, 2005). Despite the relevance of blackgram, a significant research gap persists due to the lack of spatially explicit, model-based assessments of yield potential, yield gaps, and water productivity across India's diverse agro-ecological zones. Traditional field experiments often fail to capture long-term climate variability and management interactions at regional and national scales. The current absence of studies aimed at simulating yield potential and quantifying yield gaps for blackgram in India at the regional/national scale is a major research gap for blackgram. In addition, a comprehensive water productivity atlas specifically tailored for the major blackgram growing districts across different regions of India and globally is lacking. Likewise, inadequate focus on the development of comprehensive technological and policy frameworks targeted at narrowing yield gaps and enhancing water productivity in major blackgram growing zones is another notable knowledge gap.

To address this gap, the present study employs the Agricultural Production Systems Simulator (APSIM), a process-based crop simulation model with a robust and modular architecture capable of simulating complex interactions among climate, soil, genotype, and management across diverse environments (Keating et al., 2003) which has also been tested for its robust performance under diverse

ecologies and different crops of India (Bana et al., 2023; Mohanty et al., 2012; Sneha et al., 2025). The process-based structure of APSIM enables representation of crop phenology, photoperiod sensitivity, soil water balance, and genotype-specific growth parameters, allowing realistic simulation of phenological development and yield formation in blackgram under diverse environmental conditions. By leveraging APSIM, this study adopts a multi-pronged systems approach aligned with national and global sustainability priorities. The specific objectives are: to simulate the long-term potential yield (Yp) of blackgram across twenty major growing districts representing the Central Zone (CZ), South Zone (SZ), and Western Zone (WZ) of India and to quantify the spatial heterogeneity of the yield gap (Yg) between simulated potential and realized farmer yields; to assess and spatially map total water productivity, including Physical Water Productivity (PWP), Irrigation Water Productivity (IWP), and Economic Water Productivity (EWP), thereby developing a comprehensive water productivity atlas for blackgram cultivation; to identify and prioritize dominant biophysical and managerial constraints, such as sowing time and water deficits, contributing to blackgram yield variability using multivariate statistical analysis; and to formulate zone-specific technological and policy interventions tailored to the CZ, SZ, and WZ to sustainably narrow yield gaps, enhance water productivity, and advance India toward self-reliance (*Atmanirbharta*) in pulse production. Collectively, the study supports SDG 2 (Zero Hunger), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action) by promoting climate-resilient and resource-efficient blackgram production systems (NITI Aayog, 2025).

2 Materials and methods

2.1 About the crop simulation model

The primary analytical tool for this research was the Agricultural Production Systems Simulator (APSIM), a globally validated modelling framework developed in Australia to simulate biophysical processes of farming practices (Keating et al., 2003). Its flexible "plug-in/plug-out" architecture allows the integration of diverse crop, soil, and management modules, including water balance and nutrient dynamics, making it highly adaptable across agro-ecological zones. This flexibility enabled precise calibration for India's diverse environments and supported robust estimation of the exploitable yield gap by capturing interactions among climate, soil, crop genetics, and management. APSIM's proven performance in pulse yield gap studies further reinforces its suitability for this national-scale assessment (Bhatia et al., 2006; Sarkar et al., 2024).

2.2 Study area

To ensure a comprehensive national assessment, the study focused on the primary blackgram-growing regions of India. Based on the cultivated area during the quinquennial ending 2022–23 of the Directorate of Economics and Statistics, Government of India (https://data.desagri.gov.in/website/crops-apy-report-web), twenty districts with the maximum cultivated area under blackgram have been identified, spanning three climatic buffer zones. This strategic selection ensured significant coverage of the overall cultivated area encompassing the diverse climatic buffer zones where blackgram is a major *kharif* and *rabi* season crop. The selected locations were spread across Chhatarpur, Sagar, Tikamgarh, Lalitpur, Damoh, Vidisha, Shivpuri, Panna, Datia, Satna, Jabalpur, Narsinghpur, Dharashiv, Patan (Madhya Pradesh, Uttar Pradesh, Maharashtra, Gujarat) of Central Zone (CZ); Krishna, Villupuram, Kalaburagi (Andhra Pradesh, Tamil Nadu, Karnataka) of South Zone (SZ); and Bundi, Tonk, Bhilwara (Rajasthan) of Western Zone (WZ) (Figure 1A). These districts constitute a significant share in the total blackgram cultivated area in the country.

The twenty districts selected for this study collectively represent a substantial proportion of India's blackgram cultivated area and production. According to the Directorate of Economics and Statistics, these districts account for a major share of the national blackgram-growing region and encompass diverse agro-ecological environments across the Central Zone, South Zone, and Western Zone. The selection therefore ensures adequate representation of both major production belts and climatic variability influencing blackgram productivity across India.

2.3 Weather data

A comprehensive historical daily weather dataset spanning the 20-year period from 2003–2004 to 2022–2023 was compiled for each selected location to drive the APSIM simulations. The required weather parameters included maximum and minimum temperature, rainfall, and solar radiation, which were sourced from the high-resolution gridded datasets provided by the India Meteorological Department (IMD) (Supplementary Table 1). Specifically, the study utilized daily rainfall data at a 0.25° x 0.25° resolution (Pai et al., 2014) and daily maximum and minimum temperature data at a 1.0° x 1.0° resolution (Srivastava et al., 2009). To supplement these datasets, solar radiation data were sourced from the NASA POWER, which provides reliable meteorological data derived from satellite observations. Daily surface shortwave radiation (ALLSKY_SFC_SW_DWN) was obtained from the NASA POWER database at a spatial resolution of 0.5° × 0.625° as point-based meteorological data corresponding to the geographic coordinates of each district. A critical step in the data preparation process was the conversion of this gridded data into values representative of the specific district-level administrative boundaries of the study areas. For this purpose, the Thiessen Polygon interpolation technique was employed (Thiessen, 1911).

2.4 Soil data

To accurately parameterize the soil environment for the APSIM simulations, detailed soil profile information for each selected location was sourced from established national databases (NICRA Project, 2018). This was supplemented with data from the inbuilt Indian soil database of the InfoCrop V2.1 model, developed by the Indian Agricultural Research Institute (IARI), New Delhi

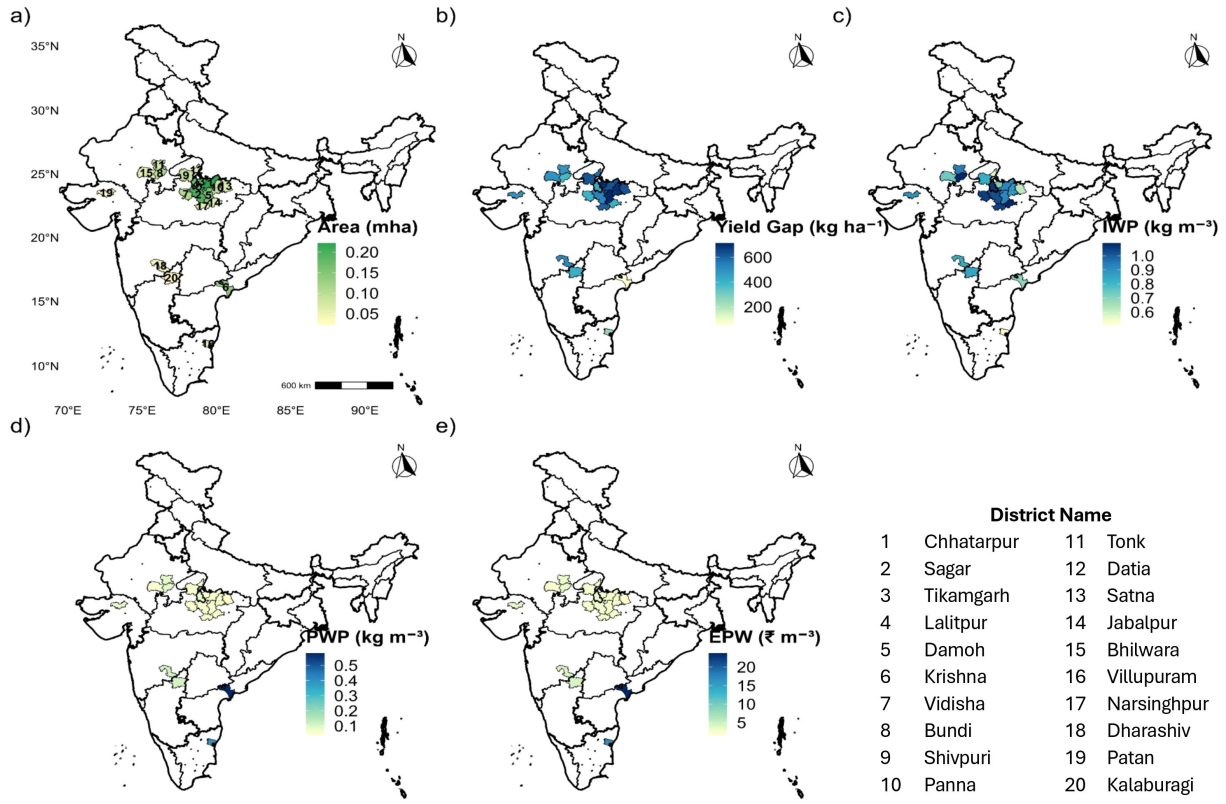


FIGURE 1
Spatial distribution of **(A)** major blackgram cultivated area, **(B)** yield gap, **(C)** irrigation water productivity (IWP), **(D)** physical water productivity (PWP), and **(E)** economic water productivity (EWP) across major blackgram-growing districts of India. Data were derived from APSIM simulations and district-level agricultural statistics (2003-2023). The figure highlights regional variability in productivity and water-use efficiency.

(https://www.quantitative-plant.org/model/InfoCrop). These databases provided the essential layer-wise soil parameters required by the model, including physical properties such as soil texture (sand, silt, and clay content), soil depth, bulk density, and key hydraulic characteristics like field capacity (drained upper limit), wilting point (crop lower limit), and hydraulic conductivity. Additionally, crucial chemical properties, including soil pH, electrical conductivity (EC), and organic carbon content, were compiled. This comprehensive soil dataset was fundamental for the model to accurately simulate the soil water balance and nutrient dynamics that govern blackgram growth and development.

2.5 Crop management information

In order to parameterize the model with realistic farming practices, crop management information was sourced from the official "package of practices" recommended by State Agricultural Universities, Krishi Vigyan Kendras (KVKs), and the respective state Departments of Agriculture for the selected districts, including research bulletins of ICAR-Indian Institute of Pulses Research (https://www.icar-iipr.org.in/). The collected data encompassed a full suite of management parameters required for the APSIM simulations. This included details on field preparation and initial soil conditions, typical planting windows, recommended seed rates and plant populations, standard inorganic fertilizer application rates, and common irrigation schedules where applicable.

2.6 Crop data/cultivar file

To ensure that the simulations accurately reflect the performance of locally adapted cultivars, the APSIM model was parameterized using specific blackgram genetic coefficients. The coefficients govern the plant's response to environmental factors, particularly thermal time and photoperiod, which dictate the duration of phenological stages such as flowering and maturity. For this study, the most relevant and widely adopted varieties for each agro ecological zone were selected: IPU 13-1 (Central Zone - CZ), VBN-8 (South Zone - SZ), and Kota Urd 3 (KPU524-65) (Western Zone - WZ). The identification of these dominant varieties was based on metrics such as maximum harvested area and breeder seed indent data to ensure regional representativeness (NAAS, 2019; SeedNet, 2022). The necessary genetic coefficients for the selected varieties were compiled from scientific publications, technical reports from agricultural universities (Chaithanya et al., 2019; Bommana Suvarchala et al., 2020; Banerjee et al., 2021a; Fozdar et al., 2022; Kumar and Kumar, 2022; Reddy et al., 2022; Sangeetha et al., 2022; Vishnu et al., 2022; Kumar et al., 2022; Kumar, 2023; Chauhan et al., 2025) and official varietal release documents from research institutes such as the ICAR-Indian Institute of Pulses Research (https://www.icar-iipr.org.in/). These coefficients provide the foundation for accurately simulating the growth, phenology, and yield dynamics of each blackgram variety under diverse environmental and management conditions.

2.7 Actual yield data

To establish the baseline for the yield gap analysis, it was necessary to compare the simulated potential yields (Yp) with the actual yields (Ya) achieved by farmers. For this purpose, district-wise observed yield data for blackgram were compiled for the last 20 years, from 2003–04 to 2022-23. This historical dataset, which provided a robust and representative benchmark of on-farm productivity, was sourced from the Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare, Government of India (https://data.desagri.gov.in/website/crops-apy-report-web).

Linear detrending was performed by fitting a straight line (ordinary least-squares regression) to the yield time series and subtracting this trend from the observed values, wherever applicable. This derives the absolute yield anomaly (detrended yield), following standard practice in agronomic time-series analysis (Ye et al., 2015; Lu et al., 2017).

$$Y_t^* = Yt - b\,(t - \bar{t})$$

Y_t^* = detrended yield in year t
Y_t = actual (observed) yield in year t
b = slope of the linear trend line obtained from regression
t = time index
$\bar{t}$ = mean of the time index values

2.8 Calibration and validation of selected varieties of blackgram in APSIM model

Model calibration was performed using experimental datasets compiled from multiple published research studies, technical reports, and experimental bulletins representing different agro-ecological environments of India. These datasets included observations related to crop phenology, biomass accumulation, and grain yield. Model validation was subsequently conducted using independent datasets obtained from the All India Coordinated Research Project (AICRP) on Pulses along with additional experimental datasets reported in scientific literature. These validation datasets represented multiple locations and seasons, ensuring spatial and environmental representativeness of model evaluation across major blackgram growing regions. Model calibration was performed using data for biomass and grain yield from 2018–2019 for KPU 524-65, 2019–2020 for VBN 8 (VBG 09-005), and 2022–2023 for IPU 13-1. Validation was conducted using independent datasets from subsequent years, i.e., 2020–2021 for KPU 524-65, 2022–2023 for IPU 13-1, and 2021–2022 for VBN 8 (VBG 09-005) at two locations Kalaburagi and Villupuram (Figure 2).

During calibration, the key genetic and physiological parameters were adjusted to achieve the best agreement between simulated and observed values for important phenological and yield attributes. The parameters influencing developmental stages (days to emergence, flowering, pod initiation, and maturity) were first calibrated, followed by those governing biomass accumulation, partitioning, and grain development. The Growing Degree Days (GDD) and thermal time concepts were used to simulate crop phenology accurately across environments. Validation was performed using independent datasets obtained from the All India Coordinated Research Project (AICRP) on Pulses, along with data compiled from relevant research papers, theses, and bulletins for the selected climatic buffer zones (Nikam, 2019; Vishnu et al., 2022; Yadav et al., 2022; Kumar, 2023; Subbiah, 2023; Gautam et al., 2024; Kaleeswari et al., 2025). These datasets were used to assess the model's capability to reliably simulate blackgram growth, and yieldunder varying environmental conditions. Model performance was evaluated using statistical criteria including the coefficient of determination (R^2), Root Mean Square Error (RMSE), Nash-Sutcliffe Efficiency (NSE), and Normalized Mean Square Error (NMSE) (Mamudu et al., 2025; Melsen et al., 2025). Higher R^2 and NSE values and lower RMSE and NMSE values indicated a strong agreement between simulated and observed results, confirming the APSIM-blackgram model's robustness and reliability in simulating blackgram performance across diverse agro-climatic conditions (Figure 2).

2.9 Simulation run

A simulation was carried out to estimate the potential yield of blackgram across the selected twenty districts of India using the APSIM-blackgram model. The model was run under potential production conditions to determine the maximum attainable yield across diverse environments. District-level simulations were conducted within the selected climatic buffer zones using long-term daily weather data, soil profile information, crop management practices, and cultivar-specific genetic coefficients. The APSIM-blackgram model was run for a 20-year period from 2003–2004 to 2022–2023 to simulate potential yield across the selected districts.

2.10 Estimation of yield potential and yield gap

To estimate the yield gap of blackgram, the simulated potential yield (Yp) obtained from the APSIM model in each period was compared with the corresponding historical observed yields (Ya), district-wise, for the period 2003–2004 to 2022-2023. The yield gap (Yg) was quantified using the formula (Manivasagam et al., 2025):

$$Yg = Yp - Ya$$

Where, Yg represents the total yield gap, Yp is the simulated potential yield, and Ya denotes the actual yield achieved by farmers.

2.11 Assessment of water productivity

Water productivity assessment was carried out using three key metrics, namely Physical Water Productivity (PWP), Irrigation Water Productivity (IWP), and Economic Water Productivity (EWP). Effective rainfall was estimated using the FAO empirical relationship, assuming that 70% of the total seasonal rainfall is considered effective rainfall for crops other than rice under Indian conditions (FAO, 1978). Physical Water Productivity was estimated as the crop yield (kg) per unit of total water consumed (m^3) (Sharma et al., 2025), expressed as:

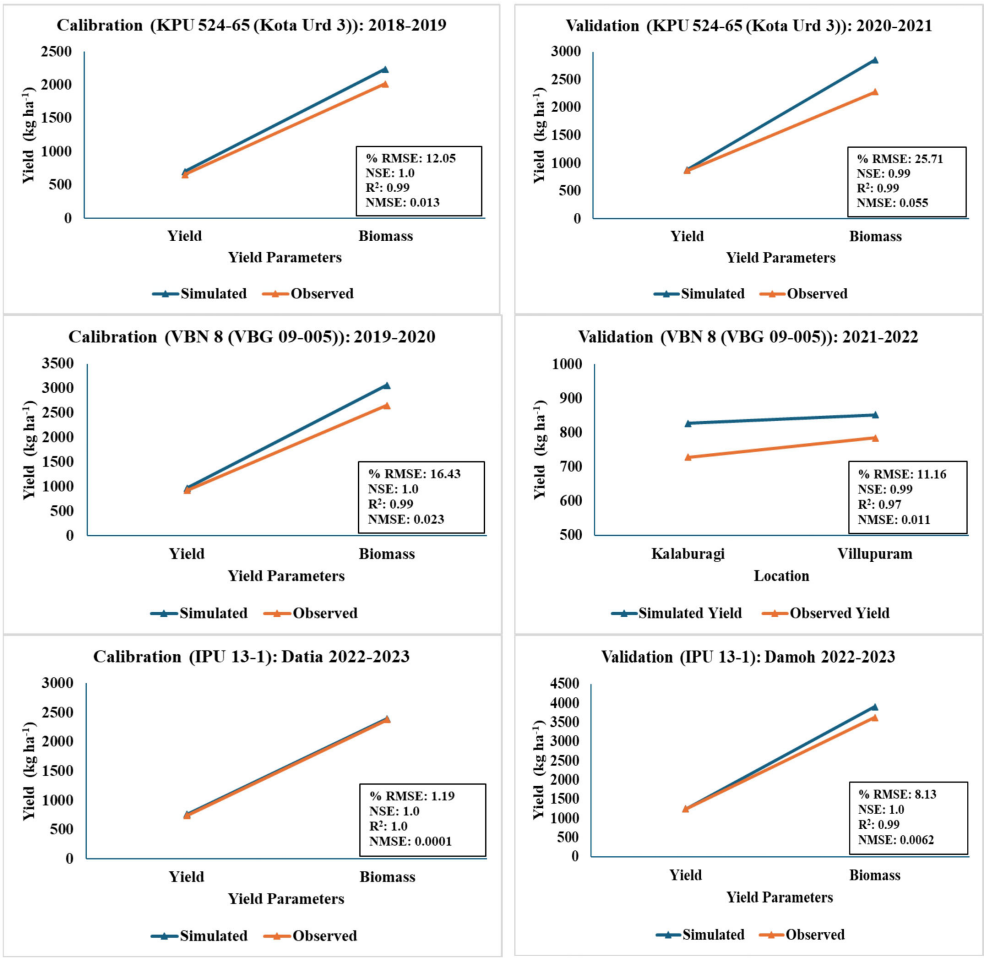


FIGURE 2
Calibration and validation of selected blackgram varieties using the APSIM model based on observed field data from different agro-climatic zones. Simulated yields and Biomass were compared with observed values to assess model performance. The close agreement indicates satisfactory model reliability.

$$\text{PWP (kg m}^{-3}) = \frac{\text{Crop Economic Yield}}{\text{Total water use}}$$

Irrigation Water Productivity was calculated as the yield per unit of irrigation water applied (m^3) (Sharma et al., 2025), using the formula:

$$\text{IWP (kg m}^{-3}) = \frac{\text{Crop Economic Yield}}{\text{Irrigation water applied}}$$

Economic Water Productivity was determined as the monetary return per unit of water consumed (m^3) (Awoke et al., 2025), given by:

$$\text{EWP (m}^{-3}) = \frac{\text{Gross Revenue}}{\text{Total water consumed}}$$

2.12 Geospatial analysis and water productivity atlas preparation

The calculated yield gaps for blackgram were spatially analyzed using GIS tools (ArcGIS) to identify regions with significant productivity gaps (Hajjarpoor et al., 2018). Administrative boundary shapefiles of the selected districts were linked with district-level productivity indicators and converted into GIS-compatible formats to generate thematic maps highlighting priority areas for improvement (Figure 1). Since the analysis was conducted using aggregated district-level indicators, spatial interpolation was not applied. Yield gap and water productivity metrics, including Physical Water Productivity (PWP), Irrigation Water Productivity (IWP), and Economic Water Productivity (EWP), were spatially mapped across major blackgram-growing regions (Figure 1). The resulting maps categorized productivity levels into relative classes (low, medium, and high) based on the distribution range of calculated values, facilitating spatial interpretation of yield gaps and water productivity patterns and supporting targeted interventions to improve water use efficiency and the sustainability of blackgram production systems.

2.13 Carbon budget estimation and sustainability metrics

District-level carbon accounting for blackgram (*Vigna mungo* L.) was conducted across twenty representative districts of India using a life-cycle-based carbon budgeting approach. Carbon input (kg CO_2

eq. ha^{-1}), representing emissions from seed, fertilizers, plant protection chemicals, field operations, and energy use, was adopted from standardized coefficients reported by Malhi et al. (2021). Carbon output (kg CO_2 eq. ha^{-1}) was estimated based on total above-ground biomass production converted into carbon equivalents (Lal, 2008). Carbon balance was computed as the difference between carbon output and carbon input. Carbon efficiency was calculated as the ratio of carbon output to carbon input, while the Carbon Sustainability Index (CSI) was derived by normalizing the carbon balance with respect to carbon input (Malhi et al., 2021). The emission coefficients adopted in this study represent generalized estimates reported in peer-reviewed literature and include emissions associated with major agricultural inputs and field operations; therefore, the carbon budgeting approach provides a comparative assessment of carbon performance across districts rather than a full life-cycle carbon inventory.

Carbon balance (kg CO_2 eq. ha^{-1}) = Carbon output - Carbon input;

Carbon efficiency = Carbon output/Carbon input;

Carbon Sustainability Index (CSI) = (Carbon output - Carbon input)/Carbon input.

2.14 Statistical analysis

To identify the primary factors influencing yield variability in blackgram, Principal Component Analysis (PCA) was employed (Sharifi et al., 2018). The PCA analysis was performed using district-level observations representing twenty locations across the three agro-ecological zones included in the study. PCA was performed using key factor categories such as soil fertility, agronomic practices (plant density, nutrient management), yield attributes (yield components) and irrigation practices. This multivariate statistical approach reduced data complexity while retaining the most significant information, enabling the identification of key factors contributing to blackgram yield variability across different regions.

3 Results

3.1 Yield gap

The comparative assessment of actual and simulated blackgram yields across twenty representative districts spanning the Central Zone (CZ), South Zone (SZ), and Western Zone (WZ) revealed pronounced spatial heterogeneity in productivity and yield gaps (Table 1; Figures 1, 3). The results highlighted substantial untapped yield potential under current production environments, with actual yields consistently lower than their simulated biophysical potential yield across all regions.

Actual yields across districts ranged from a minimum of 279.50 kg ha^{-1} in Datia (Madhya Pradesh) to a maximum of 1040.00 kg ha^{-1} in Krishna (Andhra Pradesh), reflecting the contrasting production conditions across regions. Simulated potential yields, estimated through the APSIM model under optimized conditions, varied from 840.13 kg ha^{-1} in Kalaburagi (Karnataka) to 1176.44 kg ha^{-1} in Damoh (Madhya Pradesh). This wide variation across districts signifies that the achievable potential yield of blackgram is nearly more than 100% times higher than the realized field yields in several districts.

Across all districts, the mean yield gap (the difference between simulated and actual yields) averaged approximately 515.11 kg ha^{-1}. In relative terms, the percentage yield gap varied substantially, from the narrowest gap of 5.09% in Krishna (Andhra Pradesh), where management conditions appear highly favorable, to the highest value of 67.15% in Datia (Madhya Pradesh). Districts in the Central Zone, such as Satna (66.76%), Tikamgarh (66.44%), and Panna (61.03%), also exhibited notably wide gaps, confirming a stronger influence of both agro-climatic and management factors.

Within the Central Zone (CZ), yield gaps were consistently high, ranging from 42.85% in Jabalpur to 67.15% in Datia, indicating the predominance of abiotic stress and management constraints that limit productivity. Conversely, the South Zone district of Krishna (Andhra Pradesh) exhibited the narrowest yield gap (5.09%), while another South Zone district, Villupuram (Tamil Nadu), recorded a moderate gap of 24.31%.

The variability of yield performance across sites was also reflected in the Coefficients of Variation (CV). Actual yield CVs were particularly high, ranging from 22.74% in Villupuram to 77.72% in Tikamgarh, indicating substantial year-to-year variability and instability under farmer field conditions. Collectively, these results demonstrated that blackgram productivity in India remains significantly below its attainable potential, with the average yield gap between research demonstration yields and farmers' practices estimated to be around 22% nationally, indicating considerable scope for improvement. There exists wide spatial heterogeneity in potential as well as actual yield of blackgram.

3.2 Water productivity

Substantial spatial variability in irrigation water productivity (IWP), physical water productivity (PWP), and economic water productivity (EWP) of blackgram was noted across the representative districts of major agro ecological zones (Table 2; Figures 1C–E). The overall mean IWP, PWP, and EWP were 0.86 kg m^{-3}, 0.14 kg m^{-3}, and 5.57 ₹ m^{-3}, respectively, with corresponding mean productivity gaps (IWPG, PWPG, and EWPG) of 0.98 kg m^{-3}, 0.13 kg m^{-3}, and 4.44 ₹ m^{-3}. High coefficients of variation (CVs ranging from 20.49% to 97.63%) indicate pronounced heterogeneity in both biophysical and economic water-use efficiencies across regions.

Districts in the Central Zone generally achieved the highest IWP, with Lalitpur (1.06 kg m^{-3}), Vidisha (1.05 kg m^{-3}), and Jabalpur (1.09 kg m^{-3}) performing well, reflecting efficient supplemental water use. Bundi (Rajasthan) also achieved high IWP (1.09 kg m^{-3}). However, the highest EWP (24.39 ₹ m^{-3}) was recorded in Krishna (Andhra Pradesh), which also had the narrowest IWPG (0.04 kg m^{-3}) and EWPG (1.17 ₹ m^{-3}), demonstrating highly efficient utilization of total water.

Conversely, districts in the Central Zone, such as Datia and Satna, showed low IWP (0.56 kg m^{-3} and 0.62 kg m^{-3}, respectively) and low EWP (2.88 ₹ m^{-3} and 2.30 ₹ m^{-3}, respectively), while incurring some of the largest proportional EWPGs (5.51 ₹ m^{-3} and 4.67 ₹ m^{-3},

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TABLE 1 Table representing the actual yields and simulated yields of Blackgram for the representative districts of different agro-climatic zones from 2003–2004 to 2022-2023.

Sr. no.	Parameters	Actual yield (kg/ha)	Simulated yield (kg/ha)	Yield gap (kg/ha)	% Yield gap
1	Chhatarpur, Madhya Pradesh				
	Mean	458.13	1085.46	627.33	57.79
	SD	202.74	320.86		
	CV	44.25	29.56		
2	Sagar, Madhya Pradesh				
	Mean	512.00	1039.28	527.28	50.73
	SD	259.10	360.02		
	CV	50.61	34.64		
3	Tikamgarh, Madhya Pradesh				
	Mean	355.00	1057.70	702.70	66.44
	SD	275.89	339.95		
	CV	77.72	32.14		
4	Lalitpur, Uttar Pradesh				
	Mean	527.62	946.77	419.15	44.27
	SD	214.27	293.89		
	CV	40.61	31.04		
5	Damoh, Madhya Pradesh				
	Mean	461.76	1176.44	714.68	60.75
	SD	265.89	325.72		
	CV	57.58	27.69		
6	Krishna, Andhra Pradesh				
	Mean	1040.00	1095.79	55.79	5.09
	SD	193.44	110.75		
	CV	18.60	10.11		
7	Vidisha, Madhya Pradesh				
	Mean	526.00	923.35	397.35	43.03
	SD	194.67	300.90		
	CV	37.01	32.59		
8	Bundi, Rajasthan				
	Mean	542.50	917.18	374.68	40.85
	SD	190.56	197.54		
	CV	35.13	21.54		
9	Shivpuri, Madhya Pradesh				
	Mean	413.00	1037.73	624.73	60.20
	SD	128.73	238.73		
	CV	31.17	23.01		
10	Panna, Madhya Pradesh				
	Mean	441.00	1131.54	690.54	61.03
	SD	134.34	240.43		
	CV	30.46	21.25		

(Continued)

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TABLE 1 Continued

Sr. no.	Parameters	Actual yield (kg/ha)	Simulated yield (kg/ha)	Yield gap (kg/ha)	% Yield gap
11	Tonk, Rajasthan				
	Mean	469.00	947.59	478.59	50.51
	SD	145.83	139.31		
	CV	31.09	14.70		
12	Datia, Madhya Pradesh				
	Mean	279.50	850.74	571.24	67.15
	SD	69.42	276.75		
	CV	24.84	32.53		
13	Satna, Madhya Pradesh				
	Mean	311.50	937.24	625.74	66.76
	SD	114.23	224.54		
	CV	36.67	23.96		
14	Jabalpur, Madhya Pradesh				
	Mean	543.00	950.08	407.08	42.85
	SD	222.31	297.63		
	CV	40.94	31.33		
15	Bhilwara, Rajasthan				
	Mean	368.02	858.17	490.15	57.12
	SD	189.27	172.98		
	CV	51.43	20.16		
16	Villupuram, Tamil Nadu				
	Mean	766.00	1012.07	246.07	24.31
	SD	174.17	84.88		
	CV	22.74	8.39		
17	Narsinghpur, Madhya Pradesh				
	Mean	517.50	1118.02	600.52	53.71
	SD	188.88	271.43		
	CV	36.50	24.28		
18	Dharashiv, Maharashtra				
	Mean	414.50	926.80	512.30	55.28
	SD	199.88	132.75		
	CV	48.22	14.32		
19	Patan, Gujarat				
	Mean	444.50	931.08	486.58	52.26
	SD	143.79	170.66		
	CV	32.35	18.33		
20	Kalaburagi, Karnataka				
	Mean	426.00	840.13	414.13	49.29
	SD	118.41	93.54		
	CV	27.80s	11.13		

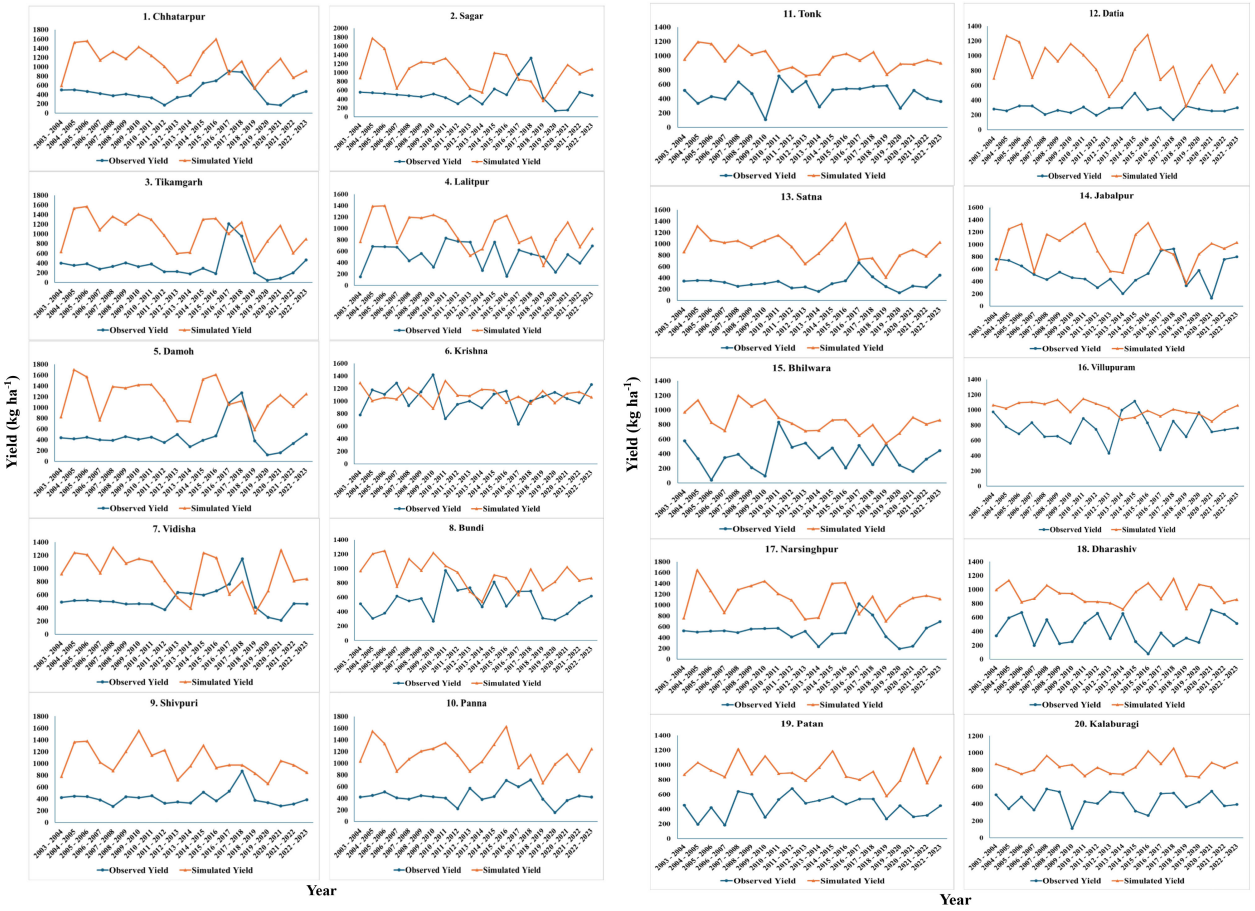


FIGURE 3
Temporal variation of simulated and observed blackgram yields across representative districts from 2003-2004 to 2022-2023. The results demonstrate the model's ability to capture inter-annual yield variability.

respectively). Dharashiv (Maharashtra) and Kalaburagi (Karnataka) also incurred high EWPGs (8.34 ₹ m^{-3} and 6.30 ₹ m^{-3}, respectively).

Overall, the Central Zone exhibited mixed results, with high potential in IWP but significant gaps in EWP in many districts. The South Zone demonstrated excellent economic returns in high-yield areas like Krishna. The observed mean productivity gaps highlight considerable potential for improving blackgram water productivity through precision irrigation, moisture conservation, and site-specific agronomic interventions.

3.3 Carbon budget estimation and sustainability metrics

Blackgram exhibited moderate spatial variability in carbon dynamics across districts, reflecting differences in productivity and management intensity (Table 3). Carbon output ranged from 4348.75 kg CO_2 eq. ha^{-1} in Datia (Madhya Pradesh) to 5981.83 kg CO_2 eq. ha^{-1} in Damoh (Madhya Pradesh), with a mean value of 5064.66 kg CO_2 eq. ha^{-1}. Correspondingly, carbon balance varied from 3731.53 kg CO_2 eq. ha^{-1} to 5364.61 kg CO_2 eq. ha^{-1}, indicating that blackgram acted as a net carbon sink across all study districts. Carbon efficiency values ranged between 7.05 and 9.69, with higher efficiencies recorded in Damoh, Panna, and Narsinghpur, while the mean CSI of 7.21 highlighted strong overall carbon sustainability. The coefficient of variation for carbon balance (10.86%) indicates relatively low regional variability, suggesting stable carbon performance across environments.

3.4 Principal component analysis

The Principal Component Analysis (PCA) was performed using district-level observations representing twenty locations across the three agro-ecological zones included in the study. The Principal Component Analysis (PCA) biplot illustrates the major patterns of variability among selected blackgram-growing districts based on soil properties, crop geometry, management practices, and yield attributes (Figure 4). The first principal component (PC1) explained 39.2% of the total variance, while the second principal component (PC2) accounted for 18.7%, together capturing 57.9% of the overall variability in the dataset, indicating a strong representation of multivariate relationships governing blackgram productivity. The district-wise biplot (Figure 4A) revealed clear separation of locations across the two principal axes, reflecting substantial heterogeneity in nutrient availability, irrigation access, and crop management practices across blackgram-growing regions. Districts such as Villupuram, Krishna, and Kalaburagi were distinctly

10.3389/fagro.2026.1775298

TABLE 2 Table representing the mean of irrigation water productivity (IWP), physical water productivity (PWP), and economic water productivity (EWP) of blackgram and their gaps for the representative districts across different agro-climatic zones from 2003–2004 to 2022-2023.

Sr. no.	Station/zone name	IWP (kg m^{-3})	IWPG (kg m^{-3})	PWP (kg m^{-3})	PWPG (kg m^{-3})	EWP (₹ m^{-3})	EWPG (₹ m^{-3})
1	Chhatarpur, Madhya Pradesh	0.92	1.25	0.09	0.14	3.68	4.73
2	Sagar, Madhya Pradesh	1.02	1.05	0.09	0.10	3.70	3.19
3	Tikamgarh, Madhya Pradesh	0.71	1.41	0.08	0.18	3.16	6.05
4	Lalitpur, Uttar Pradesh	1.06	0.84	0.11	0.10	4.22	3.38
5	Damoh, Madhya Pradesh	0.92	1.43	0.08	0.14	3.37	4.88
6	Krishna, Andhra Pradesh	0.69	0.04	0.61	0.03	24.39	1.17
7	Vidisha, Madhya Pradesh	1.05	0.79	0.08	0.07	3.44	2.17
8	Bundi, Rajasthan	1.09	0.75	0.12	0.10	4.68	3.16
9	Shivpuri, Madhya Pradesh	0.83	1.25	0.08	0.13	3.51	4.40
10	Panna, Madhya Pradesh	0.88	1.38	0.08	0.15	3.40	5.23
11	Tonk, Rajasthan	0.94	0.96	0.12	0.14	4.67	4.61
12	Datia, Madhya Pradesh	0.56	1.14	0.07	0.16	2.88	5.51
13	Satna, Madhya Pradesh	0.62	1.25	0.06	0.14	2.30	4.67
14	Jabalpur, Madhya Pradesh	1.09	0.81	0.08	0.07	3.73	2.48
15	Bhilwara, Rajasthan	0.74	0.98	0.09	0.14	3.40	4.69
16	Villupuram, Tamil Nadu	0.51	0.16	0.42	0.14	17.03	4.78
17	Narsinghpur, Madhya Pradesh	1.04	1.20	0.09	0.11	3.60	3.99
18	Dharashiv, Maharashtra	0.83	1.02	0.15	0.22	5.61	8.34
19	Patan, Gujarat	0.89	0.97	0.11	0.14	4.70	5.14
20	Kalaburagi, Karnataka	0.85	0.83	0.15	0.17	5.98	6.30
	Mean	**0.86**	**0.98**	**0.14**	**0.13**	**5.57**	**4.44**
	SD	**0.18**	**0.37**	**0.13**	**0.04**	**5.39**	**1.59**
	CV	**20.49**	**37.65**	**97.63**	**33.14**	**96.64**	**35.87**

Bold values denote summary statistics (mean, standard deviation, and coefficient of variation) for the respective parameters.

positioned on the positive side of PC1, whereas Datia, Tonk, and Dharashiv clustered on the negative side, indicating contrasting agro-ecological and management environments. The vectors represent the magnitude and direction of influence of individual parameters, including pH, OC (organic carbon), BD (bulk density), N (nitrogen), P (phosphorus), PD (plant density), RS (row spacing), SD (sowing depth), IR (irrigation), SPP (seeds per pod), PPP (pods per plant), and GY (grain yield).

PC1 (39.2%) was primarily governed by a nutrient-irrigation and yield component gradient, showing strong positive loadings for P, IR, SPP, PPP, and N, indicating that districts on the positive side of PC1 were characterized by higher nutrient availability, better moisture access, and improved reproductive traits. In contrast, pH was negatively associated with PC1, suggesting inverse relationships between soil reaction and intensively managed, high-input production systems. PC2 (18.7%) differentiated districts mainly based on grain yield and soil physical properties, with strong positive contributions from GY and OC, and moderate influence of BD and SD, while row spacing (RS) showed a negative loading. Higher positions along PC2 corresponded to districts with better yield performance and improved soil organic status, whereas lower positions were associated with wider spacing and suboptimal yield expression.

Districts located close to the origin (e.g., Bundi, Chhatarpur, and Satna) were not strongly influenced by any single parameter, indicating relatively balanced soil and management conditions. The variable contribution plot (Figure 4B) highlighted P, IR, SPP, PPP, and GY as the most influential variables shaping the first two principal components, as reflected by their longer vectors and higher contribution intensities. The small angles among P, N, IR, and SPP indicate strong positive associations, whereas their opposite orientation to pH and RS suggests trade-offs between soil chemical conditions, crop geometry, and intensification-driven yield formation in blackgram production systems. Variables such as phosphorus (P), nitrogen (N), irrigation (IR), seeds per pod (SPP), and pods per plant (PPP) contributed strongly to PC1, indicating the dominant role of nutrient availability and water management in shaping productivity differences across districts. Grain yield (GY) and soil organic carbon (OC) showed stronger associations with PC2, suggesting the importance of soil fertility status and reproductive efficiency in determining yield performance.

10.3389/fagro.2026.1775298

TABLE 3 District-level carbon balance and sustainability assessment of blackgram.

Sr. no.	District name	Carbon output (kg CO_2 eq. ha^{-1})	Carbon balance (kg CO_2 eq. ha^{-1})	Carbon efficiency	Carbon sustainability index
1	Chhatarpur, Madhya Pradesh	5531.05	4913.82	8.96	7.96
2	Sagar, Madhya Pradesh	5290.40	4673.18	8.57	7.57
3	Tikamgarh, Madhya Pradesh	5398.71	4781.49	8.75	7.75
4	Lalitpur, Uttar Pradesh	4836.60	4219.38	7.84	6.84
5	Damoh, Madhya Pradesh	5981.83	5364.61	9.69	8.69
6	Krishna, Andhra Pradesh	5623.82	5006.59	9.11	8.11
7	Vidisha, Madhya Pradesh	4714.44	4097.22	7.64	6.64
8	Bundi, Rajasthan	4778.98	4161.76	7.74	6.74
9	Shivpuri, Madhya Pradesh	5293.27	4676.05	8.58	7.58
10	Panna, Madhya Pradesh	5745.48	5128.26	9.31	8.31
11	Tonk, Rajasthan	4929.33	4312.11	7.99	6.99
12	Datia, Madhya Pradesh	4348.75	3731.53	7.05	6.05
13	Satna, Madhya Pradesh	4773.12	4155.90	7.73	6.73
14	Jabalpur, Madhya Pradesh	4844.13	4226.91	7.85	6.85
15	Bhilwara, Rajasthan	4468.22	3851.00	7.24	6.24
16	Villupuram, Tamil Nadu	5208.28	4591.06	8.44	7.44
17	Narsinghpur, Madhya Pradesh	5686.15	5068.93	9.21	8.21
18	Dharashiv, Maharashtra	4729.84	4112.62	7.66	6.66
19	Patan, Gujarat	4742.33	4125.11	7.68	6.68
20	Kalaburagi, Karnataka	4368.50	3751.28	7.08	6.08
	Mean	**5064.66**	**4447.44**	**8.21**	**7.21**
	SD	**483.07**	**483.07**	**0.78**	**0.78**
	CV	**9.54**	**10.86**	**9.54**	**10.86**

Bold values denote summary statistics (mean, standard deviation, and coefficient of variation) for the respective parameters.

3.5 Correlation-density matrix analysis

The correlation-density matrix (Figure 5) provided detailed insights into pairwise relationships among soil properties, crop geometry, yield components, and grain yield in blackgram. Organic carbon (OC) exhibited a significant positive correlation with grain yield (r = 0.604**), highlighting the role of soil organic matter in supporting yield stability. Bulk density (BD) showed a weak positive association with grain yield (r = 0.342), although this relationship was not statistically significant, suggesting that moderate soil compaction had limited influence on blackgram productivity under the studied conditions.

Strong nutrient interrelationships were evident, with nitrogen (N) and phosphorus (P) showing a highly significant positive correlation (r = 0.793***), reflecting synchronized nutrient management across districts. Both N and P were also significantly and positively associated with irrigation (IR; r = 0.793***), confirming the coupled role of water and nutrient availability in intensifying blackgram productivity. Seeds per pod (SPP) showed highly significant and positive correlations with IR (r = 0.793***) and pods per plant (r = 0.930***), identifying reproductive traits as closely linked yield components under favorable moisture regimes.

Crop geometry exerted a notable influence on yield components. Plant density (PD) was positively correlated with SPP (r = 0.521*) and PPP (r = 0.608**), indicating improved per-unit-area reproductive potential at optimal population levels. However, row spacing (RS) exhibited nonsignificant negative associations with GY (r = -0.348) and yield components, suggesting that excessively wide spacing may limit yield realization. Grain yield (GY) showed weak direct correlations with most individual yield components, implying that yield variability in blackgram was governed by an integrated interaction of nutrient availability, irrigation, and reproductive efficiency, rather than by a single trait.

The correlation matrix corroborates the PCA results, emphasizing the dominant role of nutrient-water coupling (N-P-IR), soil organic carbon, and yield component interdependence in determining blackgram productivity across diverse agro-ecological regions, while highlighting clear trade-offs between soil reaction, crop geometry, and intensification-driven yield outcomes.

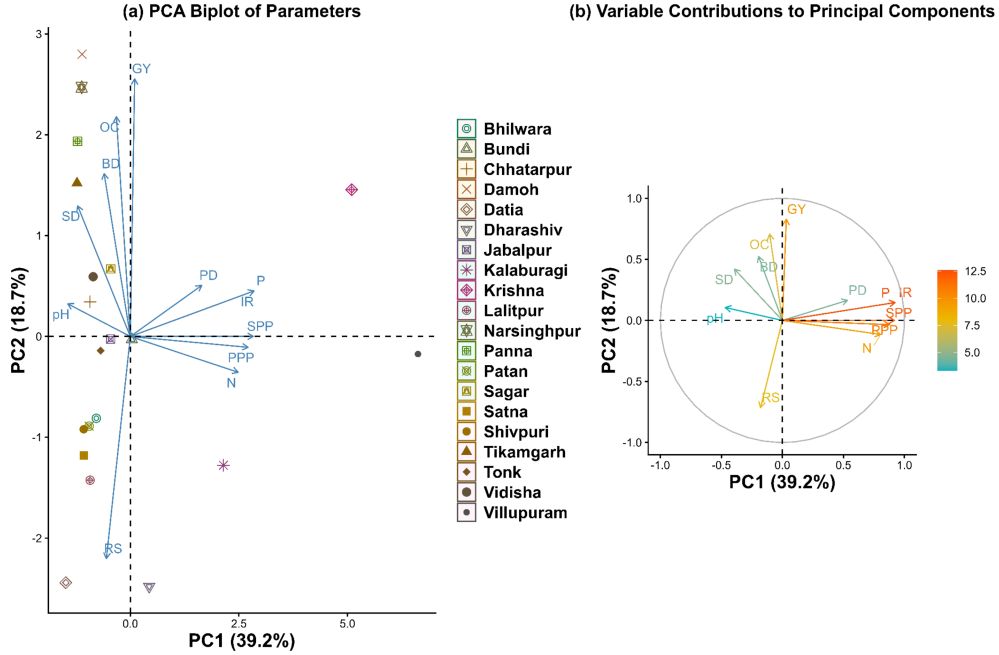


FIGURE 4
(a) Principal component analysis (PCA) biplot showing the relationships among soil properties, crop management variables, yield attributes, and grain yield across major blackgram-growing districts; **(b)** Variable contributions to the principal components (PC1 and PC2), where arrow length and direction indicate the magnitude and influence of each variable on the components. (OC, Organic Carbon; BD, Bulk Density; N, Nitrogen; P, Phosphorus; PD, Plant Density; RS, Row Spacing; SD, Sowing Depth; IR, Irrigation; SPP, Seeds Per Pod; PPP, Pods Per Plant and GY, Grain Yield).

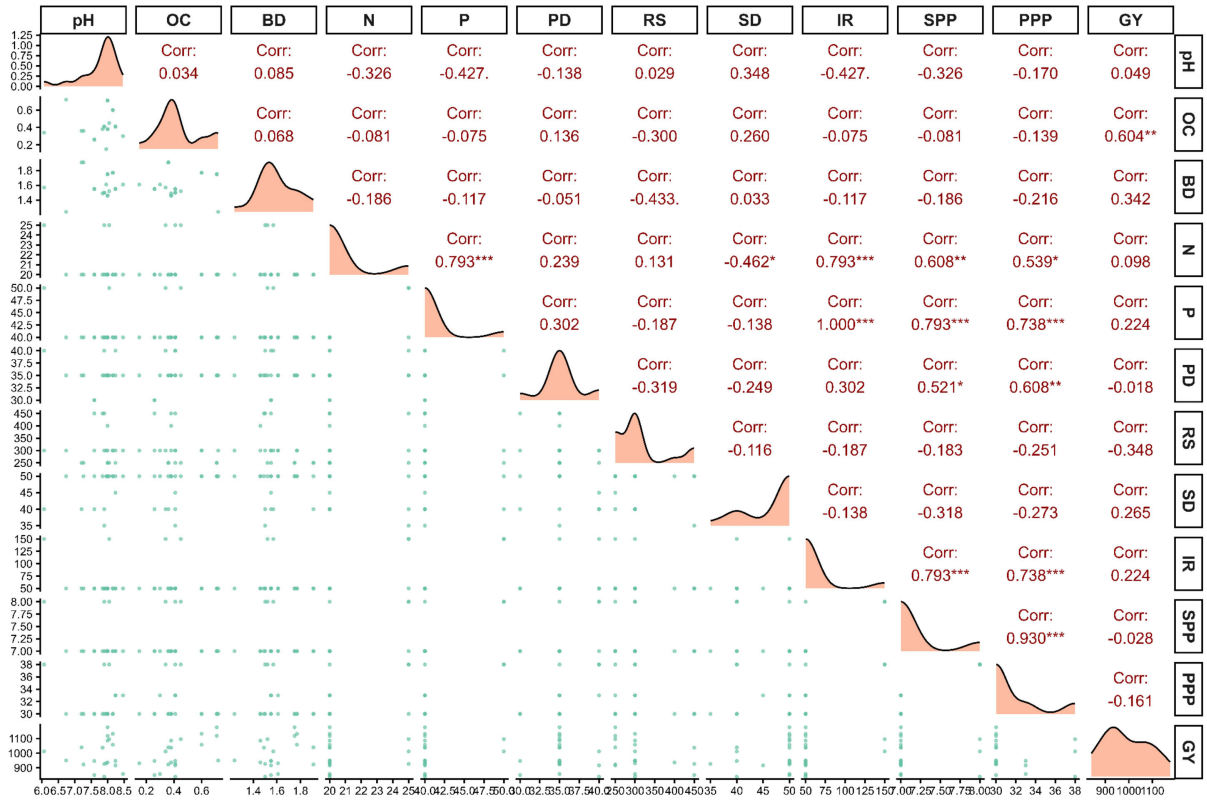


FIGURE 5
Correlation-density matrix illustrating relationships among soil characteristics, crop geometry, yield components, and grain yield in blackgram. Significant correlations indicate interactions among key factors influencing crop performance. Significance levels are indicated as *p<0.05, **p<0.01, and ***p <0.001. (OC, Organic Carbon; BD, Bulk Density; N, Nitrogen; P, Phosphorus; PD, Plant Density; RS, Row Spacing; SD, Sowing Depth; IR, Irrigation; SPP, Seeds Per Pod; PPP, Pods Per Plant and GY, Grain Yield).

4 Discussion

4.1 Yield gap

The large and persistent yield gaps observed in blackgram, particularly across the Bundelkhand region districts (Datia, Tikamgarh, Satna), are primarily attributed to its cultivation under rainfed conditions, where approximately 80% of the crop is grown in the *kharif* season. This system is characterized by erratic rainfall and low input intensity, which might have hindered in achieving the genetic potential of blackgram (Van Ittersum et al., 2013; Singh et al., 2016; Banerjee et al., 2021b). The primary constraints widening the gap include terminal heat stress and soil moisture deficits, which severely disrupt physiological processes and result in poor seed set, especially in the spring-summer season (Chauhan et al., 2010). Biotic stresses, notably Mungbean Yellow Mosaic Virus (MYMV), are also major yield-reducing factors, capable of causing yield reductions in blackgram (Sankaran et al., 2024).

The existence of a significant yield gap, between demonstration yields and actual farm yields for pulses was earlier noted implying a substantial technology adoption gap (Van Ittersum et al., 2013). Constraints cited by farmers include inadequate weed management, limited availability of improved production technologies suitable for rice-fallow systems, and poor access to quality seed and technical advisory services (Ali and Gupta, 2012; Kumar et al., 2020; ICAR-IIPR, 2022). Bridging even 50% of this gap through precision water management, improved seed systems, and capacity building about improved management practices could substantially enhance national blackgram output (Singh et al., 2016). This requires targeted interventions such as the adoption of high-yielding, disease-resistant cultivars and effective agronomic management to synchronize the crop with favorable weather windows (Chauhan et al., 2010). The PCA results highlight that nutrient availability (N and P), irrigation access, and reproductive traits (pods per plant and seeds per pod) are the dominant drivers of yield variability across districts. These findings suggest that improving nutrient-water management, optimizing crop geometry, and enhancing soil organic carbon through integrated nutrient management can significantly contribute to narrowing yield gaps and improving blackgram productivity.

4.2 Water productivity

The pronounced spatial variability in blackgram water productivity underscores the influence of both agro-climatic and management factors on crop water-use efficiency (Singh et al., 2016; Van Halsema and Vincent, 2012). The Central Zone showed relatively high IWP, suggesting that the supplemental irrigation applied is effective. The ecological service provided by blackgram's Biological Nitrogen Fixation (BNF), which might have facilitated sustained blackgram productivity (Stagnari et al., 2017).

The exceptionally high EWP observed in Krishna (Andhra Pradesh) demonstrates the potential for maximizing economic returns when high actual yields are achieved under efficient management, particularly in rice-fallow systems which utilize residual moisture (Ali and Gupta, 2012; Kumar et al., 2020). Conversely, the large economic water productivity gaps (EWPG) observed in many CZ districts (such as Datia, Dharashiv) emphasize the critical need for integrating deficit irrigation and micro-irrigation technologies to enhance returns per unit of water consumed (Fereres and Soriano, 2007; Aggarwal et al., 2019). As a crop predominantly cultivated under rainfed or residual moisture conditions, policies ensuring the judicious use of scarce blue water resources through supplemental irrigation are paramount (Van Ittersum et al., 2013). The effective implementation of the Minimum Support Price (MSP) mechanism is critical to stabilize farmers' income, ensuring that physical water gains translate into sustained economic water productivity (Reddy, 2013).

4.3 Carbon budget estimation and sustainability metrics

The consistently positive carbon balance across all districts confirms that blackgram-based production systems function as reliable net carbon sinks, primarily due to favorable biomass accumulation combined with relatively low external input requirements, as also reported for pulse-based systems by Malhi et al. (2021). Further, the highest carbon output and carbon balance were recorded in Panna signifying the positive impact of the combined influence of agroclimatic conditions and management practices contributing to higher biomass production led carbon assimilation. Higher carbon efficiency and CSI values in districts such as Damoh, Narsinghpur, and Panna indicate that efficient agronomic management and suitable agro-climatic conditions enhance carbon sustainability, corroborating earlier findings that legumes play a critical role in climate-smart agriculture through biological nitrogen fixation and reduced reliance on synthetic nitrogen fertilizers (Lal, 2016). The comparatively low spatial variability further supports observations by Smith et al. (2014) that stable pulse-based systems can contribute significantly to mitigation pathways. Overall, the results suggest that scaling blackgram cultivation, particularly in rainfed regions, can simultaneously enhance farm income while ensuring carbon sustainability.

5 Zone-wise technological and policy options for bridging yield gaps and enhancing water productivity of blackgram

Strategies are required to address the distinct constraints of the major blackgram-growing zones to accelerate production and realize the high yield potential (ICAR-IIPR, 2022) (Supplementary Table 2).

5.1 Central zone - Madhya Pradesh, Uttar Pradesh, Maharashtra, Gujarat

The Central Zone, which includes the high-gap districts of Tikamgarh, Datia, and Sagar, is characterized by large, unexploited potential yields but suffers from major constraints related to terminal stress, poor weed management, and technology adoption gaps (Singh et al., 2016).

To address these limitations, technological interventions should emphasize precision agronomic management and balanced fertilization. Priority must be given to the adoption of improved, high-yielding, and disease-resistant varieties (e.g., IPU 13-1) (ICAR-IIPR, 2022). Implementing effective weed management programs is essential to reduce the substantial yield loss associated with inadequate weed control (Ali and Gupta, 2012). Supplemental irrigation using harvested rainwater or farm ponds should be encouraged to mitigate mid-season and terminal drought stress (Subrahmaniyan et al., 2023). From a policy perspective, the Central Zone requires a cluster-based technology dissemination model through NFSM-Pulses and seed hub networks along with investments in minor irrigation and watershed projects under Pradhan Mantri Krishi Sinchai Yojana (PMKSY) (NITI Aayog, 2025). A performance-linked incentive framework rewarding higher water productivity can motivate farmers to adopt efficient irrigation systems. Strengthening procurement under MSP ensures price stability (Reddy, 2013). Improved agronomic management and yield enhancement in the Central Zone are expected to increase carbon-use efficiency of blackgram systems. Districts such as Damoh, Panna, and Narsinghpur already show relatively higher carbon efficiency and CSI values, indicating strong carbon sequestration potential. Adoption of improved cultivars, balanced nutrient management, and supplemental irrigation can therefore enhance both productivity and carbon sustainability.

5.2 South zone - Andhra Pradesh, Tamil Nadu, Karnataka

The South Zone, including the rice-fallow belts of Krishna and Villupuram, shows highly varied results, from near-zero gaps in Krishna to high gaps in Kalaburagi, but its overall potential lies in maximizing production under residual moisture conditions and mitigating MYMV and terminal heat (Subrahmaniyan et al., 2023).

To address these limitations, technological interventions should prioritize short-duration, MYMV-resistant varieties (e.g., VBN-8) suited for timely establishment in rice-fallow systems (ICAR-IIPR, 2022). The focus must be on maximizing the efficiency of residual soil moisture through conservation tillage and specialized planting techniques to reduce evaporation losses. Integrated Pest Management (IPM) strategies are crucial for controlling MYMV and insect pests such as pod borers. At the policy level, the focus should be on promoting rice-fallow intensification under the NFSM Targeting Rice Fallow Areas (TRFA) initiative, providing support for zero-tillage seed drills. Financial and input support for micro-irrigation systems through PMKSY-Per Drop More Crop is essential to address localized water constraints and maximize IWP. Strengthening farmer-producer cooperatives for seed multiplication and the timely distribution of disease-resistant seeds will mitigate losses due to biotic stress (NITI Aayog, 2025). Rice-fallow systems in the South Zone show favourable carbon dynamics due to relatively higher productivity and efficient use of residual soil moisture. Adoption of short-duration varieties, conservation tillage, and improved nutrient management can further increase biomass accumulation and carbon efficiency, strengthening the climate-smart role of blackgram in these systems.

5.3 Western zone - Rajasthan

The WZ, including districts like Bundi and Tonk, is characterized by a higher yield gap (approx. 40-57%) driven by arid climate, coarse-textured soils, and reliance on limited *kharif* rainfall, resulting in low average productivity.

To address these limitations, climate-resilient and water-efficient technologies must be prioritized. The introduction of improved, short-duration varieties (e.g., Kota Urd 3) adapted to the zone's specific soil and thermal time requirements is necessary (ICAR-IIPR, 2022). Moisture conservation practices, including mulching and broad-bed furrow systems, are essential to improve soil moisture retention under rainfed conditions. Adoption of micro-irrigation and rainwater harvesting structures at the village level can enhance irrigation water productivity (Fereres and Soriano, 2007). At the policy level, region-specific interventions should include water stewardship incentives for efficient irrigation use and financial support for micro-irrigation adoption. Strengthening Krishi Vigyan Kendras (KVKs) in arid districts for large-scale demonstrations of moisture conservation and stress-tolerant varieties is essential. In high-risk areas, weather-index-based crop insurance (PMFBY) should be expanded to safeguard farmer incomes while facilitating the adoption of improved practices (NITI Aayog, 2025). Despite semi-arid conditions, blackgram systems in the WZ maintain a positive carbon balance, indicating their potential contribution to carbon sustainability. Adoption of moisture conservation practices, improved varieties, and efficient water management can further enhance biomass production and carbon efficiency in these rainfed environments.

6 Limitations and future scope

This study relied primarily on district-level secondary datasets compiled from published sources and national databases, which may introduce some uncertainty due to the absence of uniformly available long-term experimental datasets across all locations. Carbon budgeting was estimated using standardized emission coefficients rather than site-specific measurements, while gridded weather data and district-level soil parameters may not fully capture micro-climatic and intra-district variability. Nevertheless, the long-term simulation period (2003-2023) improves the robustness of regional comparisons. Future research should evaluate APSIM alongside other crop simulation models under variable climate scenarios and integrate socio-economic drivers to better quantify technology adoption gaps and support sustainable pulse intensification.

7 Conclusion

The APSIM-based assessment demonstrates that blackgram productivity in India remains substantially below its attainable potential, with yield gaps exceeding 50% in several Central and Western Zone districts. These gaps are primarily driven by terminal

moisture and heat stress, biotic pressures, and limited adoption of improved agronomic practices under predominantly rainfed conditions. Positive carbon balance and high CSI confirm blackgram's strong potential for sustainable intensification and climate-change mitigation in Indian agriculture. The Central Zone requires priority interventions focused on improved varieties, balanced nutrient management, effective weed control, and supplemental irrigation through rainwater harvesting. In the South Zone, rice-fallow intensification using short-duration, MYMV-resistant cultivars and moisture-conservation practices offers significant scope for yield enhancement, while the Western Zone demands climate-resilient varieties and soil-water conservation strategies. Future research must conduct a sensitivity study to compare the APSIM model's predictive accuracy with other established crop simulation models, particularly under varying climatic and management scenarios. Furthermore, it is essential to integrate socio-economic factors into the yield gap analysis to rigorously quantify their contribution to the technology adoption gap.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethics and consent do not apply to the study because there are no human or animal tissues involved.

Author contributions

PD: Data curation, Methodology, Conceptualization, Investigation, Validation, Formal analysis, Writing – original draft, Visualization. PB: Formal analysis, Methodology, Conceptualization, Investigation, Supervision, Writing – review & editing. SP: Supervision, Data curation, Writing – review & editing. SSr: Writing – review & editing, Methodology. RB: Writing – review & editing, Conceptualization, Methodology, Supervision. VP: Writing – review & editing, Methodology, Visualization. BC: Methodology, Investigation, Writing – review & editing. SSu: Methodology, Conceptualization, Writing – review & editing. TJ: Writing – review & editing, Visualization.

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Conflict of interest

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fagro.2026.1775298/full#supplementary-material

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