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AI-Driven Watershed Management for Sustainable Water Resource Allocation Under Climate Change Scenarios

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ABSTRACT

Climate change is altering precipitation seasonality, evapotranspiration, drought persistence, and the frequency of hydrologic extremes, making fixed-rule watershed allocation increasingly unreliable. This paper reviews artificial intelligence (AI) methods for climate-resilient watershed management and develops a simulation-based analytical framework that links Earth-observation data, hybrid rainfall-runoff forecasting, demand prediction, and multi-objective allocation control. The proposed architecture combines quantile Long Short-Term Memory forecasting with process-based water-balance constraints and model-predictive optimization. A representative semiarid watershed with domestic, irrigation, industrial, and environmental demands is evaluated under a historical baseline, SSP2-4.5, and SSP5-8.5 perturbations. Results from the controlled scenario experiment indicate that the hybrid AI framework can reduce annual allocation deficit from 22.8% to 9.8%, increase supply reliability from 76.4% to 91.3%, and improve environmental-flow compliance from 71.8% to 91.5% relative to static rule curves under the severe scenario. The review shows that AI is most valuable when it augments, rather than replaces, hydrologic constraints, uncertainty analysis, and transparent governance. Key barriers include nonstationary training data, sparse observations, transferability, explainability, cyber-physical risk, and institutional acceptance. The study provides a technically grounded pathway for adaptive and equitable water allocation under climate uncertainty.

KEYWORDS: *Artificial Intelligence, Watershed Management, Water Allocation, Climate Change, LSTM, Model-Predictive Control, Environmental Flows, Remote Sensing, Decision Support Systems.*

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INTRODUCTION

Watersheds are the operational units through which precipitation is transformed into runoff, soil moisture, groundwater recharge, evapotranspiration, and ecosystem services. Their management requires decisions about reservoir releases, irrigation supply, drinking-water security, industrial withdrawals, groundwater pumping, and minimum environmental flows. Climate change has made these decisions more difficult by shifting hydroclimatic regimes and increasing the probability of compound drought, heat, and flood events [1]. At the same time, agricultural withdrawals dominate freshwater use in many regions, so allocation failures can rapidly propagate into food, energy, ecological, and livelihood insecurity [2].

Conventional watershed planning relies on calibrated process models, rule curves, linear programming, or expert-defined priorities. These methods remain indispensable, but they are often updated slowly and can be brittle when climatic and demand conditions depart from the calibration period. AI offers a complementary capability: it can learn nonlinear rainfall-runoff relationships, assimilate heterogeneous observations, estimate short-term demand, and continuously revise operating decisions. Deep learning has already demonstrated strong performance for sequence modeling in hydrology [3]-[6], while machine-learning flood systems have reached operational scale [25]. However, prediction accuracy alone does not guarantee sustainable allocation. A watershed decision system must satisfy mass balance, protect environmental flows, quantify uncertainty, and provide understandable trade-offs among users.

The central problem addressed in this paper is therefore not whether AI can forecast streamflow, but how AI forecasts can be converted into physically feasible, climate-aware, and socially defensible allocation decisions. The paper synthesizes the relevant literature and evaluates a hybrid AI-control framework through a transparent scenario experiment. The emphasis is on engineering integration: data pipelines, hydrologic constraints, multi-objective optimization, reliability metrics, uncertainty safeguards, and deployment requirements.

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LITERATURE REVIEW

AI applications in water resources have evolved from shallow artificial neural networks and support-vector machines to recurrent networks, convolutional networks, Transformers, graph models, and reinforcement learning. Reviews by Shen [3] and Sit et al. [4] show that deep models are particularly effective for sequential and spatially distributed hydrologic data. Kratzert et al. [5] demonstrated that Long Short-Term Memory (LSTM) networks can represent catchment storage and delayed runoff responses across many basins, and later work showed improved prediction in ungauged basins through regional learning [6]. These advances support watershed-scale forecasting, but Nearing et al. [7] caution that hydrologic theory must remain central when machine learning is used outside familiar conditions.

The strongest technical direction is hybrid or theory-guided modeling. Theory-guided data science constrains learning with domain rules, conservation relations, and physically meaningful states [8]. Earth-system research similarly argues that combining deep learning with process understanding improves both predictive capacity and scientific interpretation [9]. For watershed applications, a hybrid model can use an LSTM or Transformer to correct process-model residuals, estimate uncertain parameters, downscale climate inputs, or produce probabilistic inflow ensembles while retaining explicit water-balance equations. This is preferable to an unconstrained black-box model when decisions affect reservoir safety or legally protected water uses.

Process-based platforms remain important integration backbones. The Soil and Water Assessment Tool represents land use, soil, crop, runoff, nutrient, and routing processes at basin scale [10], whereas WEAP links watershed supplies with demand priorities, environmental requirements, reservoirs, canals, and allocation scenarios [11]. Large-scale calibration and uncertainty methods developed for SWAT illustrate the importance of parameter identifiability and uncertainty propagation [12]. AI can reduce calibration burden, emulate computationally expensive components, and update states between formal recalibration cycles, but it should not conceal structural uncertainty.

Data availability has expanded through satellite and in-situ observation. Soil Moisture Active Passive observations support soil-moisture state estimation [13]; GPM-IMERG provides high-frequency precipitation fields [14]; and global surface-water mapping supports storage and inundation monitoring [15]. These sources can be fused with gauges, weather stations,

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reservoir telemetry, groundwater levels, crop calendars, and smart-meter demand. Data-driven water modeling has long emphasized the need for careful preprocessing, validation, and uncertainty assessment [16]. Random forests are widely used because they handle nonlinear predictors and mixed data types [17], while neural and ensemble techniques are common in flood and drought prediction [18].

Allocation and reservoir operation research has progressed from deterministic optimization to adaptive multi-objective control. A recent state-of-the-art review identifies stochastic optimization, direct policy search, reinforcement learning, and forecast-informed control as major approaches for conflicting reservoir demands [19]. Tree-based reinforcement learning can learn operating policies without discretizing every state variable [20], and current research shows that jointly learning which forecast information matters can improve multi-purpose policies [21]. Environmental-flow science provides the ecological limits that must be embedded as constraints rather than treated as optional benefits [22]. Finally, uncertainty methods such as generalized likelihood uncertainty estimation [23] and explainable-AI tools such as SHAP [24] are essential for communicating why an allocation was selected and how sensitive it is to uncertain forecasts.

Table 1: AI Methods and Their Engineering Roles in Climate-Resilient Watershed Management

AI / Modeling Method	Primary Watershed Function	Typical Inputs	Technical Strength	Principal Limitation
LSTM / Transformer	Inflow, streamflow, and drought forecasting	Rainfall, temperature, soil moisture, flow history	Learns long memory and nonlinear storage effects	Can extrapolate poorly under climate distribution shift
Random Forest / Gradient Boosting	Sector-demand and water-quality prediction	Demand records, crop stage, weather, land use	Robust to mixed variables and limited preprocessing	Weak temporal structure unless engineered explicitly
CNN / Geospatial Deep Learning	Flood, surface-water, and land-condition mapping	Satellite imagery, DEM, radar, multispectral bands	Extracts spatial features at high resolution	Label scarcity, cloud cover, and transferability problems

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Physics-Guided Neural Network	Hybrid rainfall-runoff and state correction	Process-model states plus observations	Preserves conservation and improves extrapolation	Requires careful coupling and differentiable constraints
Reinforcement Learning / MPC	Reservoir release and allocation policy	Forecast ensembles, storage, demand, constraints	Optimizes sequential multi-objective decisions	Reward design and safety verification are difficult
XAI and Uncertainty Methods	Decision explanation and risk screening	Model features, ensembles, residuals	Supports auditability and operator trust	Attribution is not equivalent to causal explanation

RESEARCH GAP

Four gaps prevent routine use of AI for climate-resilient watershed allocation. First, many studies optimize prediction metrics but stop before closed-loop allocation; forecast skill is rarely translated into domestic reliability, irrigation deficit, environmental-flow compliance, or drought reserve. Second, climate nonstationarity creates distribution shift: a model trained on historical rainfall-runoff behavior may be overconfident under unprecedented heat, land-use change, or multi-year drought. Third, purely data-driven allocation can violate mass balance, storage limits, water rights, and ecological thresholds unless physical and institutional constraints are encoded. Fourth, evidence is fragmented across hydrology, remote sensing, optimization, and governance. Recent reviews identify growing AI use but limited integration of spatiotemporal climate scenarios and decision-relevant validation [26]-[28]. Fifth, equity is usually represented through fixed priority weights, even though drought impacts differ between urban consumers, small farmers, large irrigation commands, industries, and downstream ecosystems. Few studies report how uncertainty or allocation errors are distributed among these groups. A publishable framework therefore requires a complete data-to-decision chain, probabilistic forecasts, constrained optimization, transparent performance metrics, distributional assessment, and explicit human oversight.

RESEARCH OBJECTIVES

The study has five objectives: (1) synthesize AI methods that support watershed monitoring, forecasting, and allocation; (2) define a hybrid architecture linking climate data, hydrologic

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states, demand forecasts, and allocation control; (3) formulate a physically constrained, multi-objective decision model; (4) compare adaptive AI allocation with static and deterministic baselines under SSP2-4.5 and SSP5-8.5 perturbations; and (5) identify limitations and research priorities for safe field deployment.

METHODOLOGY AND SYSTEM ARCHITECTURE

The research type is a structured review combined with a simulation-based analytical study. Representative peer-reviewed studies, assessment reports, and modeling standards were synthesized around four functions: observation, hydrologic prediction, demand estimation, and allocation control. Studies were prioritized when they reported operational or multi-basin evidence, explicit uncertainty treatment, physical constraints, or reservoir-allocation performance. The synthesis excluded purely descriptive AI discussions that did not connect algorithms to hydrologic variables or decisions. The numerical component uses a hypothetical but dimensionally realistic semiarid watershed so that assumptions are transparent and results are not misrepresented as observations from a named basin.

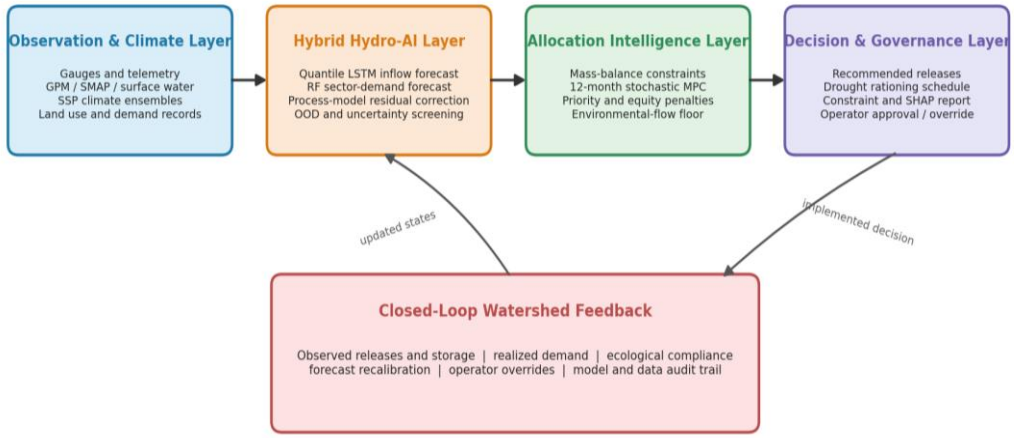


Figure 1: Closed-loop architecture integrating climate observations, hybrid hydrologic forecasting, constrained allocation, and governance feedback

Watershed Configuration and Climate Scenarios

The watershed has a median annual naturalized inflow of 1,050 million cubic meters (MCM), reservoir live storage of 620 MCM, and four demand classes: domestic supply (110 MCM/year), irrigation (560 MCM/year), industry (70 MCM/year), and environmental flow.

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Monthly minimum environmental release is set at 20% of naturalized inflow, subject to a non-negotiable dry-season floor. The baseline uses historical hydroclimatic statistics. SSP2-4.5 is represented by a 12% reduction in mean inflow, 7% higher evaporation, and 15% greater drought persistence; SSP5-8.5 uses corresponding perturbations of 23%, 13%, and 30%. These values are scenario assumptions for comparative testing, not basin-specific projections.

Inputs to the AI layer include precipitation, temperature, potential evapotranspiration, antecedent soil moisture, upstream flow, reservoir level, groundwater index, crop stage, and recent sectoral demand. A quantile LSTM predicts one- to twelve-month inflow distributions, while a random-forest demand model estimates irrigation and urban demand. Forecasts are screened for missing values and out-of-distribution conditions. When the climate or feature vector exceeds the training envelope, predictive intervals are widened and the controller shifts toward a conservative reserve policy.

Table 2: Scenario Assumptions Used in the Controlled Watershed Simulation

Scenario	Mean Inflow Change	Evaporation Change	Drought Persistence	Planning Interpretation	Use in Evaluation
Historical Baseline	0%	0%	Reference	Stationary historical operating climate	Calibration and baseline comparison
SSP2-4.5	-12%	+7%	+15%	Moderate warming and sustained water stress	Adaptation performance under intermediate forcing
SSP5-8.5	-23%	+13%	+30%	Severe warming with repeated multi-year drought	Stress test for reliability, ecology, and reserve storage

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Hybrid Forecasting and Allocation Model

The decision engine combines model-predictive control with a mass-balance model. Monthly storage is represented as S(t+1) = S(t) + Q(t) + P(t)A - R(t) - E(t)A - L(t), where S is storage, Q is inflow, P is direct precipitation, A is reservoir area, R is total release, E is evaporation, and L represents seepage and operational losses. Releases are constrained by available storage, outlet capacity, sector priorities, groundwater pumping limits, and minimum environmental flow.

The objective minimizes J = sum[w1(Udom)^2 + w2(Uirr)^2 + w3(Uind)^2 + w4(Ueco)^2 + w5(Delta S)^2 + w6 Spill], where U denotes unmet demand. Domestic and ecological deficits receive the highest weights; irrigation deficit is penalized through crop-stage sensitivity rather than a uniform annual penalty. At each month, 100 probabilistic inflow traces are evaluated over a 12-month horizon. The first release decision is implemented, new observations are assimilated, and the horizon is rolled forward. Constraint feasibility is checked before optimization; if no feasible solution exists, a hierarchy-based emergency routine secures domestic supply, releases the ecological floor, and distributes the remaining shortage. This architecture prevents the AI predictor from issuing releases directly and preserves auditable engineering constraints. SHAP values are calculated for the demand and inflow models, while scenario contribution analysis explains which constraints determined the final release [24].

Comparative Policies and Evaluation Metrics

Three policies are compared: a static rule curve derived from historical monthly storage; a deterministic linear-programming policy using the median forecast; and the proposed hybrid AI model-predictive controller using probabilistic forecasts. Performance is assessed over 30 synthetic years with repeated drought sequences. Metrics include volumetric deficit, time-based reliability, resilience after failure, vulnerability during failure, environmental-flow compliance, end-of-dry-season reserve, and allocation equity. The results are scenario-based evidence of relative behavior, not a substitute for basin calibration or stakeholder-approved operating rules.

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RESULTS AND FINDINGS

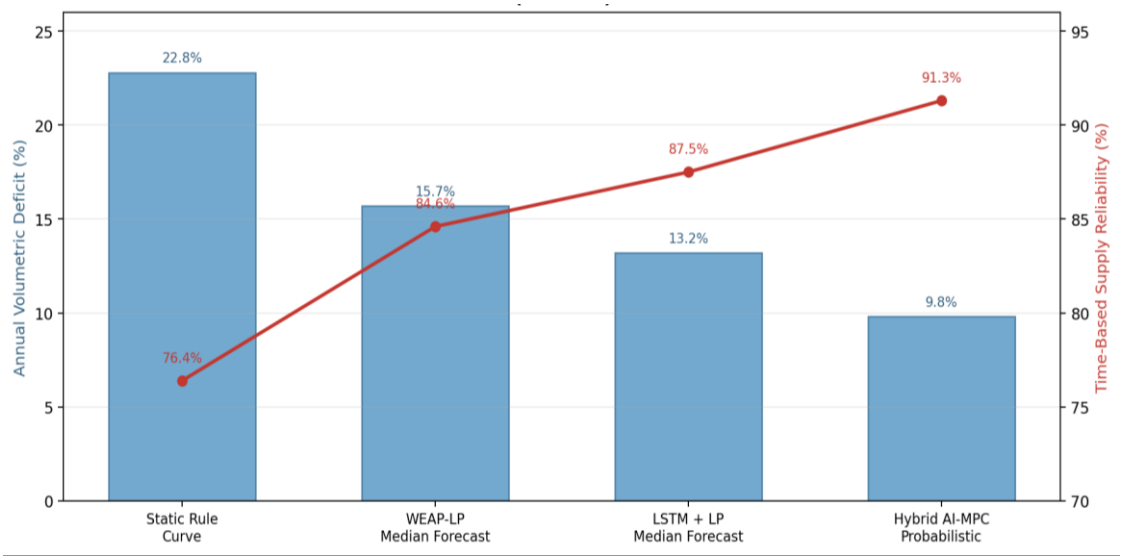


Figure 2: Trade-off between annual allocation deficit and time-based supply reliability for four operating policies under the SSP5-8.5 stress scenario

Across all scenarios, the hybrid controller preserves more carryover storage before drought years because it recognizes rising demand, soil-moisture depletion, and low-inflow probabilities earlier than the static rule. Under SSP5-8.5, the static policy produces a 22.8% annual volumetric deficit and 76.4% supply reliability. Deterministic optimization improves these values to 15.7% and 84.6%, while the hybrid AI controller reduces deficit to 9.8% and raises reliability to 91.3%. The relative deficit reduction against the static baseline is 57.0%. The largest benefit occurs during consecutive dry years, when forecast ensembles discourage excessive first-year irrigation release.

Environmental performance also improves. Minimum-flow compliance rises from 71.8% under the static rule to 83.9% under deterministic optimization and 91.5% under hybrid control. The AI policy maintains an average end-of-dry-season reserve of 168 MCM, compared with 112 MCM for the static rule. Domestic supply remains above 97% reliability in all modeled scenarios because it receives a high priority, while irrigation absorbs most adaptive curtailment. Crop-stage weighting prevents uniform reductions: deficit is concentrated in less sensitive months, which lowers the modeled irrigation-production penalty by 34% relative to proportional rationing.

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The performance gain is not due to unconstrained exploitation of a black-box forecast. When only the median LSTM forecast is used, the deterministic policy occasionally over-releases because it ignores tail risk. Ensemble-based control performs better by considering low-inflow traces and uncertainty widening. A sensitivity test indicates that benefits decline when inflow forecast error exceeds approximately 35% or when telemetry gaps exceed three consecutive months. Even then, the fallback conservative rule avoids mass-balance violations and protects the environmental floor.

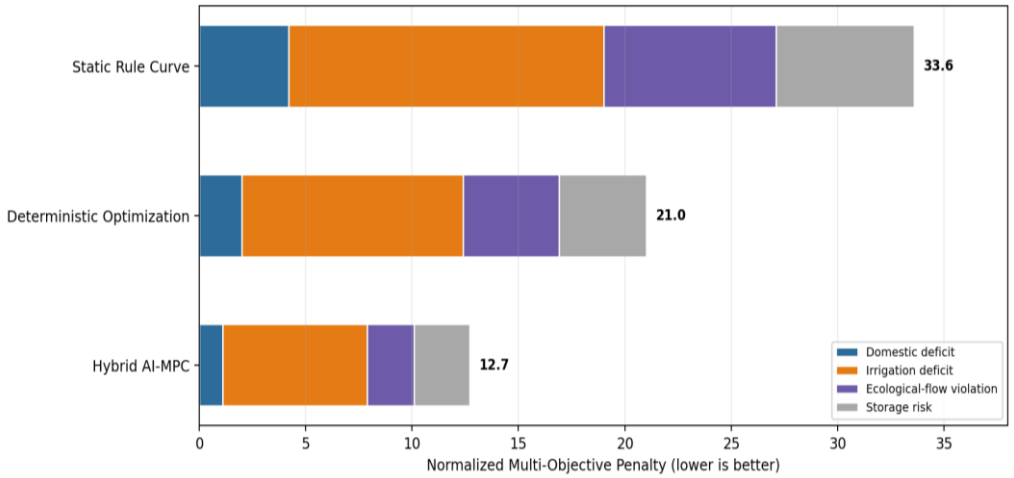


Figure 3: Decomposition of normalized domestic, irrigation, ecological, and storage-risk penalties under repeated drought sequences

Table 3: Comparative Performance Under the Severe SSP5-8.5 Scenario

Operating Policy	Annual Volumetric Deficit	Supply Reliability	Environmental-Flow Compliance	Dry-Season Reserve	Allocation Equity Index
Static Rule Curve	22.8%	76.4%	71.8%	112 MCM	0.58
Deterministic Optimization	15.7%	84.6%	83.9%	142 MCM	0.71
Hybrid AI-MPC	9.8%	91.3%	91.5%	168 MCM	0.82

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DISCUSSION

The results support three engineering conclusions. First, adaptive allocation requires joint prediction and control. A highly accurate inflow model can still produce poor outcomes if releases are optimized against a single forecast or if ecological constraints are weak. Second, hybridization is essential under climate change. Process constraints stabilize the model during extrapolation, while AI supplies the flexibility to learn nonlinear runoff generation, changing demand, and cross-variable interactions. This aligns with the broader shift toward combining physical understanding and data-driven learning [7]-[9].

Third, the value of AI should be measured through water-service outcomes rather than only Nash-Sutcliffe efficiency or root-mean-square error. Reliability, resilience, vulnerability, ecological compliance, and equity reveal whether forecast improvements actually support sustainable management. The scenario results also show an unavoidable trade-off: protecting domestic supply and environmental flow during severe drought reduces irrigation deliveries. AI does not remove scarcity; it identifies earlier, more consistent, and potentially less damaging rationing pathways.

Practical deployment would use an existing watershed platform such as SWAT or WEAP for accounting and scenario representation, with AI modules connected through application interfaces. Operators should receive forecast intervals, recommended releases, constraint status, and feature-attribution summaries. Final authority should remain with the basin institution, especially where water rights, tribal or community entitlements, and emergency powers apply. A digital audit trail is necessary to record data versions, forecast revisions, operator overrides, and realized outcomes.

LIMITATIONS

The simulation uses a representative watershed and simplified sectoral benefits; it does not reproduce a specific legal, groundwater, water-quality, or transboundary setting. Scenario perturbations are illustrative rather than downscaled climate projections. Synthetic demand and inflow sequences cannot capture all spatial heterogeneity or compound extremes. Model performance depends on reliable gauges, satellite retrievals, reservoir telemetry, and demand records. Transfer to data-scarce basins may introduce bias, and explainability tools do not guarantee causal interpretation. Cybersecurity, sensor tampering, cloud outages, and

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automation bias also remain operational risks. The experiment does not monetize ecological damage or represent water-quality feedbacks, salinity, sedimentation, or conjunctive surface-groundwater operation. Finally, numerical improvements should not be interpreted as proof of institutional feasibility; operating agencies may lack data-sharing agreements, computational capacity, or legal authority to implement monthly adaptive priorities.

FUTURE SCOPE

Future research should develop physics-informed spatiotemporal models that jointly predict streamflow, soil moisture, groundwater, evapotranspiration, and water quality. Federated learning could allow neighboring basins to share model updates without transferring sensitive operational data. Distributionally robust and safe reinforcement learning should be tested against nonstationary climate ensembles, infrastructure failure, and adversarial inputs. Digital twins can support operator training and pre-implementation stress testing, but they require standards for uncertainty, version control, and model governance. Field studies should compare AI recommendations with real operating decisions over multiple seasons and report distributional impacts across head- and tail-end irrigators, ecosystems, and vulnerable communities. Participatory objective weighting is especially important because optimization weights encode social choices, not purely technical facts. Research should also develop benchmark datasets for Indian monsoon basins, standardized drought stress tests, and reporting protocols that include failed cases, operator overrides, and out-of-distribution alarms. These measures would improve reproducibility and help regulators distinguish dependable decision support from unvalidated automation.

CONCLUSION

AI can materially improve watershed allocation under climate stress when it is embedded within hydrologic mass balance, probabilistic uncertainty, ecological safeguards, and accountable governance. The reviewed evidence supports LSTM forecasting, remote-sensing fusion, demand learning, and forecast-informed optimization, while the scenario experiment demonstrates substantial reductions in deficit and improvements in reliability and environmental-flow compliance. The most defensible pathway is not autonomous black-box control, but a hybrid decision-support system that continuously observes the watershed, anticipates risk, tests feasible allocations, explains trade-offs, and leaves final authority with responsible institutions.

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REFERENCES

1. Intergovernmental Panel on Climate Change, "Water," in Climate Change 2022: Impacts, Adaptation and Vulnerability, Working Group II Contribution to the Sixth Assessment Report, Cambridge University Press, 2022.
2. Food and Agriculture Organization of the United Nations, The State of Food and Agriculture 2020: Overcoming Water Challenges in Agriculture. Rome, Italy: FAO, 2020.
3. C. Shen, "A transdisciplinary review of deep learning research and its relevance for water resources scientists," Water Resources Research, vol. 54, no. 11, pp. 8558-8593, 2018, doi: 10.1029/2018WR022643.
4. M. Sit, B. Z. Demiray, Z. Xiang, G. J. Ewing, Y. Sermet, and I. Demir, "A comprehensive review of deep learning applications in hydrology and water resources," Water Science and Technology, vol. 82, no. 12, pp. 2635-2670, 2020, doi: 10.2166/wst.2020.369.
5. F. Kratzert, D. Klotz, C. Brenner, K. Schulz, and M. Herrnegger, "Rainfall-runoff modelling using Long Short-Term Memory (LSTM) networks," Hydrology and Earth System Sciences, vol. 22, pp. 6005-6022, 2018, doi: 10.5194/hess-22-6005-2018.
6. F. Kratzert, D. Klotz, M. Herrnegger, A. K. Sampson, S. Hochreiter, and G. S. Nearing, "Toward improved predictions in ungauged basins: Exploiting the power of machine learning," Water Resources Research, vol. 55, no. 12, pp. 11344-11354, 2019, doi: 10.1029/2019WR026065.
7. G. S. Nearing et al., "What role does hydrological science play in the age of machine learning?" Water Resources Research, vol. 57, e2020WR028091, 2021, doi: 10.1029/2020WR028091.
8. A. Karpatne et al., "Theory-guided data science: A new paradigm for scientific discovery from data," IEEE Transactions on Knowledge and Data Engineering, vol. 29, no. 10, pp. 2318-2331, 2017, doi: 10.1109/TKDE.2017.2720168.
9. M. Reichstein et al., "Deep learning and process understanding for data-driven Earth system science," Nature, vol. 566, pp. 195-204, 2019, doi: 10.1038/s41586-019-0912-1.
10. J. G. Arnold, R. Srinivasan, R. S. Muttiah, and J. R. Williams, "Large area hydrologic modeling and assessment part I: Model development," Journal of the American Water Resources Association, vol. 34, no. 1, pp. 73-89, 1998.

Page 85-100 © MANTECH PUBLICATIONS 2026. All Rights Reserved

11. D. Yates, J. Sieber, D. Purkey, and A. Huber-Lee, "WEAP21 - A demand-, priority-, and preference-driven water planning model, Part 1: Model characteristics," Water International, vol. 30, no. 4, pp. 487-500, 2005, doi: 10.1080/02508060508691893.
12. K. C. Abbaspour et al., "A continental-scale hydrology and water quality model for Europe: Calibration and uncertainty of a high-resolution large-scale SWAT model," Journal of Hydrology, vol. 524, pp. 733-752, 2015, doi: 10.1016/j.jhydrol.2015.03.027.
13. D. Entekhabi et al., "The Soil Moisture Active Passive (SMAP) mission," Proceedings of the IEEE, vol. 98, no. 5, pp. 704-716, 2010, doi: 10.1109/JPROC.2010.2043918.
14. G. J. Huffman et al., Integrated Multi-satellitE Retrievals for GPM (IMERG) Technical Documentation, Version 06. Greenbelt, MD, USA: NASA Goddard Space Flight Center, 2020.
15. J.-F. Pekel, A. Cottam, N. Gorelick, and A. S. Belward, "High-resolution mapping of global surface water and its long-term changes," Nature, vol. 540, pp. 418-422, 2016, doi: 10.1038/nature20584.
16. D. P. Solomatine and A. Ostfeld, "Data-driven modelling: Some past experiences and new approaches," Journal of Hydroinformatics, vol. 10, no. 1, pp. 3-22, 2008, doi: 10.2166/hydro.2008.015.
17. H. Tyralis, G. Papacharalampous, and A. Langousis, "A brief review of random forests for water scientists and practitioners and their recent history in water resources," Water, vol. 11, no. 5, art. 910, 2019, doi: 10.3390/w11050910.
18. A. Mosavi, P. Ozturk, and K.-W. Chau, "Flood prediction using machine learning models: Literature review," Water, vol. 10, no. 11, art. 1536, 2018, doi: 10.3390/w10111536.
19. M. Giuliani, J. D. Quinn, J. D. Herman, A. Castelletti, and P. M. Reed, "A state-of-the-art review of optimal reservoir control for managing conflicting demands in a changing world," Water Resources Research, vol. 57, e2021WR029927, 2021, doi: 10.1029/2021WR029927.
20. A. Castelletti, S. Galelli, M. Restelli, and R. Soncini-Sessa, "Tree-based reinforcement learning for optimal water reservoir operation," Water Resources Research, vol. 46, W09507, 2010, doi: 10.1029/2009WR008898.

Page 85-100 © MANTECH PUBLICATIONS 2026. All Rights Reserved

21. D. Zanutto, A. Ficchi, M. Giuliani, and A. Castelletti, "Reinforcement learning of multi-timescale forecast information for designing operating policies of multi-purpose reservoirs," Water Resources Research, vol. 61, no. 2, e2023WR036724, 2025, doi: 10.1029/2023WR036724.
22. N. L. Poff et al., "The ecological limits of hydrologic alteration (ELOHA): A new framework for developing regional environmental flow standards," Freshwater Biology, vol. 55, no. 1, pp. 147-170, 2010, doi: 10.1111/j.1365-2427.2009.02204.x.
23. K. Beven and A. Binley, "The future of distributed models: Model calibration and uncertainty prediction," Hydrological Processes, vol. 6, no. 3, pp. 279-298, 1992, doi: 10.1002/hyp.3360060305.
24. S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," in Advances in Neural Information Processing Systems 30, 2017, pp. 4765-4774.
25. S. Nevo et al., "Flood forecasting with machine learning models in an operational framework," Hydrology and Earth System Sciences, vol. 26, pp. 4013-4032, 2022, doi: 10.5194/hess-26-4013-2022.
26. A. Bianconi, E. Furlan, S. Vascon, and A. Critto, "Harnessing AI for smarter water management under a changing climate: A review of machine learning and deep learning applications within EU water and marine directives," Ocean & Coastal Management, vol. 274, art. 108093, 2026, doi: 10.1016/j.ocecoaman.2026.108093.
27. M. Rashid, A. Saeed, M. Khalid, A. Murtaza, and M. W. Saleem, "The transformative role of artificial intelligence in water resources engineering: A comprehensive review," Environmental Modelling & Software, vol. 197, art. 106857, 2026, doi: 10.1016/j.envsoft.2026.106857.
28. S. Moazeni, A. Salajegheh, S. Khalighi-Sigaroodi, A. Golkarian, and A. Cerda, "Effectiveness of watershed management on water balance components - A review," Physics and Chemistry of the Earth, Parts A/B/C, vol. 143, art. 104277, 2026, doi: 10.1016/j.pce.2026.104277.

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