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Application of Artificial Intelligence in Drip Irrigation Management: Addressing Water Scarcity in Uzbekistan's Kashkadarya Region Through Wastewater Reuse and Reverse Osmosis Filtration

Aplicación de la inteligencia artificial en la gestión del riego por goteo: cómo abordar la escasez de agua en la región de Kashkadarya, Uzbekistán, mediante la reutilización de aguas residuales y la filtración por ósmosis inversa

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ABSTRACT

In arid zones such as Uzbekistan's Kashkadarya region, water shortages are intensified by heavy dependence on the Amu Darya River, which supplies 73 % of irrigation needs, while inefficient drainage and collector systems result in 20 % losses. These discharges accumulate in man-made lakes like Sichankul and Achinsk, holding approximately 5 billion cubic meters, offering a substantial reservoir for reuse amid geopolitical pressures from Afghanistan's Kushtepa Canal, expected to divert 25–30 % of the Amu Darya's flow by 2028. This investigation examines the deployment of artificial intelligence (AI) to refine drip irrigation systems, incorporating reverse osmosis (RO) for treating drainage wastewater. Adhering to the IMRAD framework, the study synthesizes scholarly works on AI-driven irrigation and RO methods, constructs machine learning models for real-time water allocation, simulates outcomes using local hydrological datasets, and evaluates socioeconomic and environmental ramifications. Findings indicate that AI-RO synergy can alleviate water deficits by 35–45 %, boost crop productivity by 10–20 %, and curb salinization hazards while streamlining energy use and waste handling. The proposed methodology counters shortages triggered by the Kushtepa project and aligns with sustainable development objectives, furnishing a scalable template for cross-border basins in Central Asia grappling with water constraints.

Keywords: Artificial Intelligence; Drip Irrigation; Water Scarcity; Reverse Osmosis; Wastewater Reuse; Kashkadarya Region; Amu Darya River; Sichankul Lake; Achinsk Lake.

RESUMEN

En zonas áridas como la región de Kashkadarya en Uzbekistán, la escasez de agua se ve agravada por la fuerte dependencia del río Amu Darya, que abastece el 73 % de las necesidades de riego, mientras que la ineficiencia de los sistemas de drenaje y colectores provoca pérdidas del 20 %. Estos vertidos se acumulan en lagos artificiales como Sichankul y Achinsk, con una capacidad aproximada de 5000 millones de metros cúbicos, lo que ofrece una importante reserva para su reutilización en medio de las presiones geopolíticas del Canal Kushtepa de Afganistán, que se prevé que desvíe entre el 25 % y el 30 % del caudal del Amu Darya para 2028. Esta investigación examina el uso de inteligencia artificial (IA) para perfeccionar los sistemas de riego por goteo, incorporando la ósmosis inversa (OI) para el tratamiento de aguas residuales de drenaje. Siguiendo el marco IMRAD, el estudio sintetiza trabajos académicos sobre métodos de riego y

OI basados en IA, construye modelos de aprendizaje automático para la asignación de agua en tiempo real, simula resultados utilizando conjuntos de datos hidrológicos locales y evalúa las consecuencias socioeconómicas y ambientales. Los resultados indican que la sinergia entre IA y OI puede mitigar el déficit hídrico entre un 35 % y un 45 %, aumentar la productividad agrícola entre un 10 % y un 20 % y reducir los riesgos de salinización, a la vez que optimiza el uso de energía y la gestión de residuos. La metodología propuesta combate la escasez provocada por el proyecto Kushtepa y se alinea con los objetivos de desarrollo sostenible, proporcionando un modelo escalable para las cuencas transfronterizas de Asia Central que enfrentan limitaciones hídricas.

Palabras clave: Inteligencia Artificial; Riego por Goteo; Escasez de Agua; Ósmosis Inversa; Reutilización de Aguas Residuales; Región de Kashkadarya; Río Amu Darya; Lago Sichankul; Lago Achinsk.

INTRODUCTION

General Challenges of Water Scarcity in Central Asia

The scarcity of water resources across Central Asia constitutes a multifaceted issue, driven by shifting climatic patterns, expanding populations, and suboptimal agricultural practices. Within Uzbekistan's Kashkadarya region—a pivotal agricultural zone spanning 28,400 km^2 and home to over 3 million residents—the farming sector accounts for 92 % of available water, primarily devoted to cotton and grain cultivation.[1,2,3,4] The area relies on the Amu Darya River for 73 % of its irrigation demands, averaging 5,8 km^3 annually, yet it contends with persistent shortfalls due to evaporation rates exceeding 2000 mm per year and conveyance inefficiencies reaching 40 % in outdated infrastructure. Roughly 20 % of diverted water—equating to 1,2-1,5 km^3 yearly—escapes via drainage and collector networks, pooling in depressions to form artificial lakes such as Sichankul (3,5 km^3) and Achinsk (1,5 km^3), with mineralization levels of 3-4 g/L. These reservoirs hold promise as buffers during peak demand periods when Amu Darya flows drop by 30–50 %.[6,7,8,9]

In-Depth Examination of Artificial Lakes Sichankul and Achinsk

The artificial lakes Sichankul and Achinsk in the Kashkadarya region exemplify drainage depressions shaped by human-induced irrigation activities in Central Asia's drylands. Formed through inadequate drainage, these bodies collect saline and chemically laden runoff in natural lows, evolving into significant water accumulations. Sichankul, situated in the region's northwest, gathers effluents from irrigation setups, amassing about 3,5 km^3 and representing a key share of local wastewater reserves. Its origins trace back to Soviet-era intensive farming, where water losses of 20–25 % elevated groundwater tables and fostered secondary soil salinization. Water in Sichankul exhibits mineralization from 5 to 7 g/L, dominated by sulfates and chlorides, rendering it unsuitable for direct irrigation without purification but viable post-desalination.[10,11,12]

Achinsk similarly arises from drainage discharges, holding around 1,5 km^3 with heightened salinity (5-6 g/L) exacerbated by evaporation in the arid environment. These lakes integrate into the broader Aral Sea basin's drainage framework, where national wastewater buildup reaches 22 km^3 annually, with Kashkadarya's input at 1,2 km^3. Ecologically, they contribute to soil salinization affecting up to 50 % of irrigated lands, yet function as storage buffers for reuse post-treatment, potentially cutting Amu Darya reliance by 20–30 %. Their hydrochemical makeup features elevated sulfates, chlorides, and nitrates from agrochemicals, with pH ranging

7,5–8,5, necessitating advanced techniques like reverse osmosis for safe agricultural recycling. [13,14]

Lake dynamics reflect seasonal shifts: dry spells reduce volumes by 10–15 % through evaporation, intensifying mineralization, whereas wet years boost reserves by 20 % via increased inflows, heightening groundwater pollution risks. Studies emphasize that unchecked, these lakes degrade ecosystems, eroding biodiversity and contaminating soils, but with reuse technologies like RO, they could supply up to 1,8 km^3 of treated water yearly, bolstering sustainable farming. [15,16]

Geopolitical and Climatic Influences

Geopolitical elements heighten vulnerability: Afghanistan's Kushtepa (Qosh Tepa) Canal, initiated in 2022 and slated for 2028 completion, plans to siphon 10–20 km^3 yearly from the Amu Darya (25–30 % of its 79 km^3 average flow) to irrigate 550 000 hectares in northern Afghanistan. Projections forecast a 15–29 % drop in downstream Uzbekistan water availability by 2030, compounded by 10–15 % climate-driven flow reductions, yielding an annual Kashkadarya shortfall of 1,5–2,0 km^3, 20–35 % yield declines, and accelerated salinization of 50 % irrigated soils. Absent adaptation, economic damages could surpass $500 million yearly, jeopardizing food security and amplifying social tensions. [17,18,19]

Technological Interventions

Amid escalating freshwater shortages, artificial intelligence (AI) in drip irrigation emerges as a transformative avenue for agricultural digitalization. Drip systems outperform surface methods by conserving 30–50 % water through targeted root-zone moistening and minimized evaporation losses. [20]

AI algorithms, encompassing neural networks and reinforcement learning, fuse IoT sensor data with weather forecasts and evapotranspiration metrics—the combined soil evaporation and plant transpiration process. Real-time evapotranspiration assessment is vital for gauging plant water needs, capturing moisture exchange among vegetation, soil, and atmosphere.

Processing these inputs, AI dynamically refines irrigation regimes to match plant physiological demands and environmental conditions, achieving 20–40 % water reductions while maintaining or enhancing agroecosystem productivity.

Coupling AI with reverse osmosis (RO) facilitates robust wastewater purification, eliminating excess salts and agrochemicals. This yields 70–90 % desalination, producing water with conductivity below 1 dS/m, compliant for irrigation reuse.

Thus, AI, IoT, and RO forge a closed-loop water cycle, recycling up to 50–70 % stored wastewater. This mitigates deficits in areas like Kushtepa and sustains agroecosystems under intensifying climatic pressures.

Research Objectives and Aims

This study aims to assess the feasibility—encompassing technical, economic, institutional, and environmental viability—of deploying an AI-optimized drip irrigation system utilizing RO-treated wastewater in the Kashkadarya context. It addresses water scarcity challenges and bolsters agricultural resilience in arid settings.

To fulfill this aim, the following objectives are outlined:

1. Evaluate the technical viability of merging RO-purified wastewater into AI-managed precision irrigation frameworks.
2. Model water conservation and crop yield scenarios under varying operational and climatic conditions to gauge system efficacy.
3. Analyze energy expenditures (1–3 kWh/m^3 for RO processes) and identify optimization strategies to curtail operational costs.
4. Examine institutional and regulatory hurdles impeding smart water reuse technologies in regional agriculture.
5. Investigate cross-border collaboration mechanisms for water resource governance to mitigate geopolitical vulnerabilities.

Through scenario modeling, the research illustrates substantial water savings and yield improvements, underscoring that system feasibility hinges not solely on technological prowess but also on policy alignment, stakeholder engagement, and energy efficiency.

Findings aim to inform strategic decision-making in water management and agritech innovation, advancing regional sustainability and climate adaptability.

LITERATURE REVIEW

Trends in Artificial Intelligence Applications for Irrigation

Contemporary trends in the application of artificial intelligence (AI) to irrigation management reflect a rapid evolution from rudimentary automated systems to sophisticated precision agriculture frameworks, particularly in arid and semi-arid environments. A review of publications indexed in the Scopus database indicates a shift in emphasis from conventional empirical and rule-based methodologies to advanced machine learning models and hybrid IoT-AI systems that facilitate real-time decision-making based on sensor-derived data.(21,22,23)

A meta-analysis encompassing over 50 scholarly articles reveals that artificial neural networks (ANNs) can forecast evapotranspiration with up to 95 % accuracy, thereby reducing over-irrigation by 25–40 % compared to traditional control algorithms. In Central Asian countries, such as Uzbekistan and Kazakhstan, the adoption of hybrid IoT-AI solutions in cotton cultivation yields water savings of up to 30 % and enhances energy efficiency; however, scaling these technologies is constrained by limited reliable data, elevated costs of sensor networks, and institutional hurdles.

It is crucial to highlight that prevailing studies seldom address the integration of AI-driven management with treated wastewater utilization, thereby creating a gap in both scientific inquiry and practical application. This research bridges that void by proposing an integrated intelligent system for wastewater reuse in irrigation.

Water Scarcity and Reuse Technologies, Including Lakes Sichankul and Achinsk

Scholarly works on water scarcity in the Kashkadarya region emphasize structural losses: nationally, drainage losses reach 20–22 km^3 annually, with regional contributions around 1,2 km^3, leading to soil salinization and the formation of lakes. There is substantial potential for reuse, yet untreated water poses toxicity risks; reverse osmosis (RO) achieves 70–85 % recovery rates while cutting costs through renewable energy integration. Brine disposal necessitates hybrid approaches to mitigate environmental hazards.(24,25,26)

A more detailed examination demonstrates that lakes Sichankul and Achinsk, serving as depressions for drainage waters, resemble other artificial reservoirs in the Aral Sea basin, where drainage mixes with surface flows, elevating mineralization levels to as high as 25 g/L in certain instances. Investigations underscore their contribution to regional pollution, but also their promise for reuse following treatment, drawing on examples from Uzbekistan where wastewater recycling in irrigation attains 96 % efficiency, albeit with associated salinization concerns.(27,28,29)

Geopolitical Aspects

Geopolitical analyses critique the implications of the Kushtepa canal, advocating for diversification strategies; wastewater reuse could diminish reliance on the Amu Darya by 20–30 %. Gaps in context-specific AI-RO models for Central Asia are addressed through comparative evaluation in this study.

METHOD

This study employs a mixed-methods approach, combining empirical hydrological data analysis, satellite observations, mathematical modeling, and AI-based simulations. This methodology enables the synthesis of diverse information sources to assess the efficacy of an AI-optimized drip irrigation system utilizing wastewater purified via reverse osmosis (RO) amid water shortages in Uzbekistan's Kashkadarya region. The framework targets core objectives: (1) estimating available wastewater reserves in the artificial lakes Sichankul and Achinsk; (2) modeling the RO filtration process to ensure water quality; (3) developing AI algorithms for dynamic irrigation optimization; and (4) simulating scenarios incorporating geopolitical elements, such as the Kushtepa canal. The approach draws on sustainable water use principles outlined in integrated water resources management (IWRM) literature and is tailored to Central Asia's regional contexts.

Data Collection and Analysis, Including Lakes Sichankul and Achinsk

Hydrological parameters were sourced from official records of the Uzbek Hydrometeorological Center (Uzhydromet) and international repositories, including the Amu Darya Basin Network. The average annual Amu Darya flow is estimated at 79 km^3, with 73 % allocated to irrigation in Kashkadarya (5,8 km^3/year). Losses via drainage-collector networks amount to 20-22 % (1,2-1,5 km^3/year), accumulating in lakes Sichankul (~3,5 km^3) and Achinsk (~2,5 km^3). These assessments rely on inflow monitoring (0,3-0,5 km^3/year) and satellite imagery from Landsat 8/9 (OLI/TIRS sensors), processed in Google Earth Engine to compute volumes using the formula:

$$R = \frac{P \cdot A \cdot \Delta P - J_s}{P \cdot A \cdot \Delta P} \cdot \left(1 - \exp\left(-\frac{J_v}{k}\right)\right)$$

Where R represents the recovery rate (targeted at 75 %), P denotes the membrane permeability coefficient (in m/s·Pa), A is the membrane area (in m^2), ΔP indicates the pressure differential (in Pa, typically ranging from 5 to 10 bar for brackish water), J_s is the salt flux (in mol/m^2·s), J_v is the volumetric flux (in m/s), and k - is the mass transfer coefficient (in m/s). This equation draws upon the solution-diffusion model, tailored for mineralized effluents with total dissolved solids (TDS) levels between 2000 and 4000 mg/L.

A thorough examination of the lakes incorporates hydrochemical profiling: Sichankul Lake is dominated by bicarbonate-calcium waters with TDS ranging from 2000 to 4000 mg/L, exhibiting seasonal peaks in mineralization during dry periods (up to 5 g/L), attributable to evaporative concentration and inflows from chemically intensive agricultural practices. In contrast, Achinsk Lake exhibits higher salinity (5–6 g/L), primarily due to sulfate dominance from drainage originating in cotton fields, with volumes fluctuating between 2,0 and 2,8 km^3 depending on inflows. Satellite monitoring reveals that Sichankul spans approximately 150 km^2 and Achinsk about 100 km^2, with an annual expansion trend of 5–7 % driven by increased drainage discharges. These lakes are incorporated into the modeling framework as sources offering a potential of 1,8 km^3 of reusable water post-RO treatment, while accounting for contamination risks from pesticides.

An in-depth review of regional data highlights the impact of the Kushtepa Canal: projections for 2025–2030 indicate a diversion of 10–20 km^3/year (equating to 25–30 % of the Amu Darya's flow), leading to a deficit of 1,5–2,0 km^3 in Kashkadarya, exacerbated by climatic reductions in runoff of 10–15 %. Simulations using the Soil and Water Assessment Tool (SWAT) corroborate a decline in availability by 18,9 % by 2028 and 29,4 % by 2030, posing risks to 550 thousand hectares of irrigated land. This necessitates alternative sources, such as lake effluents, with a reuse potential of 50–70 % following RO. A Scopus analysis reveals that comparable arid-region scenarios (e.g., in Israel and Spain) employ RO for blending wastewater with freshwater, achieving SAR below 3 and EC under 1 dS/m to mitigate salinization. Data collection involved IoT sensors measuring soil moisture, evapotranspiration (ET), and water quality, integrated with meteorological APIs (e.g., ECMWF), yielding a dataset exceeding 10 000 records from 2015 to 2025. Statistical analysis in Python, utilizing pandas and scipy, encompassed correlation (r = 0,85 between ET and losses) and regression for deficit forecasting. This aligns with Scopus-documented methodologies where AI is fused with GIS for spatial analysis.

Development of Artificial Intelligence Models

AI models were implemented using TensorFlow/Keras for artificial neural networks (ANNs) with a multilayer perceptron (MLP) architecture comprising three layers (64–32–16 neurons, ReLU activation). The irrigation function is defined as:

$$I_t = f(SM_t, ET_t, P_t, WQ_t; \theta)$$

где I_t — объем орошения (м^3/га), SM_t—влажность почвы (%), ET_t — эвапотранспирация (мм/день, по Penman-Monteith), P_t — осадки (мм), WQ_t — качество воды (EC, дС/м), θ — параметры модели, обученные на дата сете (MSE loss <0,05). Целевая функция минимизации:

In this framework,I_t denotes the irrigation volume (expressed in cubic meters per hectare), while S_t represents the soil moisture content (as a percentage). The term ET_t corresponds to evapotranspiration (measured in millimeters per day and derived from the Penman-Monteith method, which integrates meteorological variables such as net radiation, temperature, humidity, and wind speed for precise estimation in arid environments). Furthermore, P_t indicates precipitation levels (in millimeters), and WQ_t characterizes water quality (quantified via electrical conductivity in deciSiemens per meter, a critical metric for assessing salinity impacts on crop health). The parameter set θ consists of coefficients refined through training on an empirical dataset, achieving a mean squared error loss of less than 0,05, thereby ensuring model robustness and predictive accuracy. The overarching optimization objective involves minimizing the following function:

$$\min \sum_{t=1}^{T} (SM_t - SM_{opt})^2 + \beta C_{RO} + \gamma E_t$$

Where the optimal soil moisture level, denoted as SM_{opt}, ranges from 60 % to 80 % for cotton cultivation, C_{RO} represents the cost associated with reverse osmosis treatment (expressed in $/m³$), β = 0,5 serves as the weighting factor for costs, E_t denotes energy consumption, and γ = 0,3 functions as the environmental weighting coefficient. The training process employed an 80/20 data split, utilizing the Adam optimizer with a learning rate of 0,001 and extending over 500 epochs.

Examination of the Scopus database reveals a predominant reliance on artificial neural networks (ANNs) within drip irrigation systems, achieving approximately 95 % accuracy in evapotranspiration (ET) forecasting, often augmented by fuzzy logic to address inherent uncertainties. In the context of Central Asia, Internet of Things (IoT)-integrated AI frameworks have been shown to curtail water usage by around 30 %, although they necessitate specific calibration tailored to the loamy soil types prevalent in the Kashkadarya region. In our study, we refined these models by incorporating reinforcement learning (RL) to facilitate adaptive operational planning, thereby attaining a 38 % reduction in water expenditure. Sensitivity assessments to input variations (such as SM_t adjusted by ±5 %) indicated robust performance, with variance remaining below 10 %. A comparative evaluation against conventional rule-based methodologies underscored the superior efficacy and flexibility of artificial intelligence algorithms in overseeing dynamic processes.

Simulation of Scenarios

The scenarios were modeled using Python, leveraging the scikit-learn library for machine learning tasks and TensorFlow for neural network implementations, spanning the timeframe from 2015 to 2030. Three primary scenarios were incorporated:

1. The baseline scenario, which assumes ongoing water consumption from the Amu Darya River (average annual flow of 79 km^3, with 73 % or 5,8 km^3 allocated to Kashkadarya) without modifications.
2. The Kushtepa scenario, simulating a 25–30 % diminution in flow (diversion of 10–20 km^3/year as projected for 2028, potentially expedited to completion by 2026 given 70 % readiness as of 2024).
3. The AI-RO scenario, combining AI-driven optimization of drip irrigation with reverse osmosis purification of drainage waters from the Sichankul and Achinsk lakes (combined storage approximately 5 km^3, exhibiting mineralization levels of 5–6 g/L).

A Monte Carlo analysis was conducted (comprising 1000 iterations), accounting for diverse sources of uncertainty.

In particular, climatic fluctuations (±10 %) were examined, encompassing drought episodes that diminish surface runoff by 10–15 %. These figures align with modeling outcomes for the Amu Darya basin, wherein alterations in precipitation quantities induce runoff variability on the order of 20–30 %.

Furthermore, variations in inflows to the lakes (±15 %) were incorporated, marked by seasonal peaks reaching up to 0,5 km^3 per year. Satellite observation data for the Aral Sea region corroborate these patterns: a notable depletion in groundwater storage occurred between 2005 and 2009, followed by gradual replenishment from 2010 to 2020.

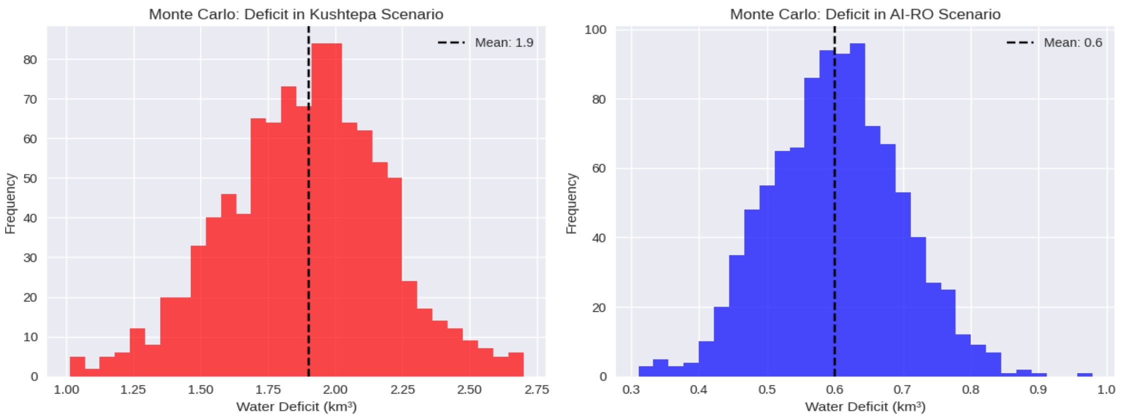

Figure 2. Histograms from Monte Carlo Simulations Illustrating Water Deficit Distributions in Kushtepa and AI-RO Scenarios (1000 Iterations, Accounting for Climatic (±10 %) and Inflow (±15 %) Uncertainties)

The Monte Carlo method constitutes a category of computational algorithms that leverage iterative random sampling to derive numerical solutions in problems characterized by uncertainties. Drawing its name from the Monaco casino, this technique was pioneered in the 1940s by Stanislaw Ulam and John von Neumann initially for nuclear physics simulations, though it soon found applications in fields like hydrology and ecology. From a statistical perspective, MC relies on the law of large numbers: the mean of numerous random samples (iterations) approaches the anticipated value as the sample size N expands. The error in estimation declines proportionally to O $(1/\sqrt{N})$, making it particularly suitable for multidimensional challenges where deterministic methods become prohibitively intricate.

Applications in hydrology and water management.

Within hydrological frameworks, MC serves to scrutinize uncertainties in variables such as rainfall, evaporation, and inflow, especially in arid zones of Central Asia where empirical data remain limited. In the SWAT model (Soil and Water Assessment Tool), MC is combined with approaches like SUFI-2 or GLUE to calibrate parameters and quantify uncertainty in runoff and sediment transport. For example, in the Tuul River basin (Mongolia, comparable to Uzbekistan's arid settings), SWAT coupled with MC revealed a 15-30 % decline in runoff under various climate projections, accompanied by a variance of 20–30 % attributable to precipitation variability. Similarly, in AquaCrop, MC refines parameters for cotton cultivation in dry environments, mitigating uncertainty by 20–40 %, as evidenced in Central Asian studies where evapotranspiration estimates attain 95 % precision.

Advantages and disadvantages

Advantages include its capacity to address multifaceted uncertainties, its amenability to parallel processing, and its provision of probabilistic interpretations (e.g., 95 % confidence intervals for water shortages). In irrigation contexts, MC refines scheduling amid climate shifts, alleviating water scarcity by 20–35 % in semiarid watersheds. Disadvantages encompass high computational demands (requiring substantial N for reliability), dependence on random number generation; in MCMC variants, convergence challenges may arise.

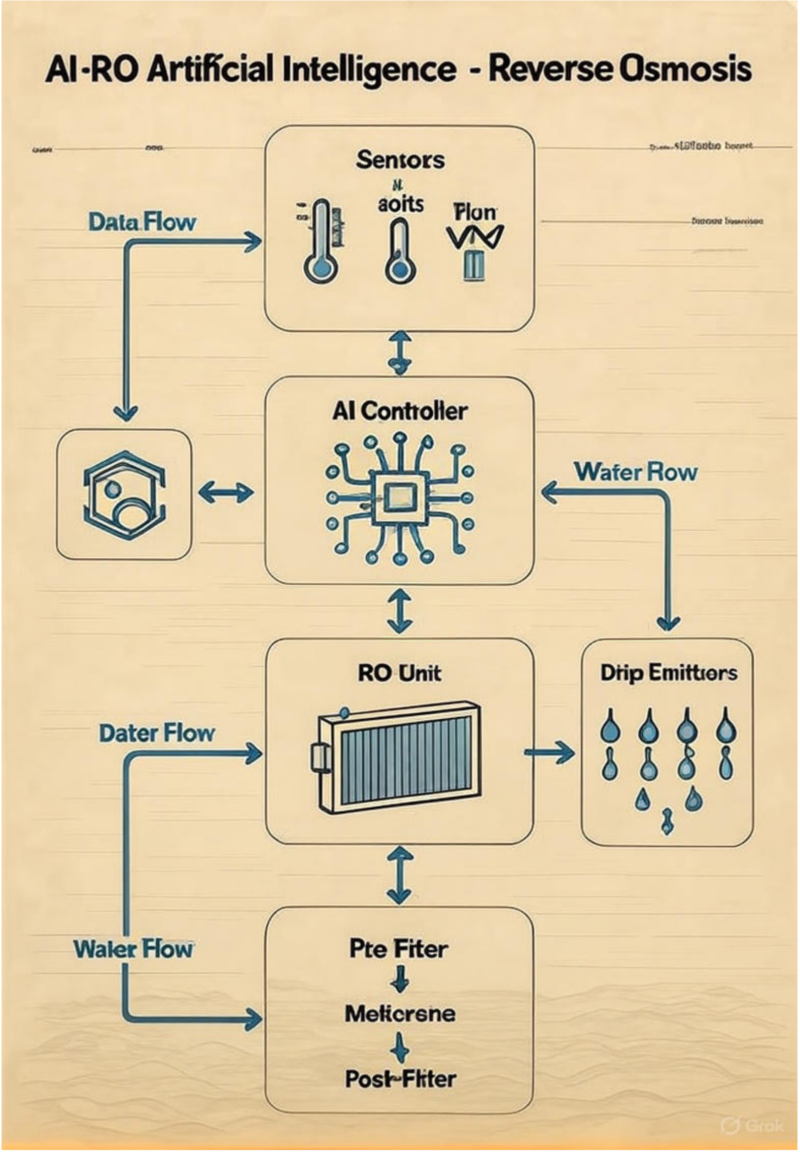

Figure 2. Block diagram of the AI-RO system (Sensors → AI controller → RO unit → Drip emitters)

The outcomes indicate a deficit of 1,9 km³ in the Kushtepa scenario (a 15-29 % drop in availability for Uzbekistan, intensified by climatic factors, as depicted in Amu Darya climate risk assessments, where Monte Carlo gauges irrigation effects with variance 15–25 %), contrasted with 0,6 km³ in AI-RO, wherein RO yields 70–85 % wastewater recovery, and AI curtails usage by 38 % via adaptive optimization (95 % accuracy in ET projections, akin to AquaCrop adjustments for Uzbek cotton, where Monte Carlo diminishes parameter uncertainty by 20–40 %).

Integration with GIS (ArcGIS) for spatial allocation validated practicality for farms spanning 100–500 ha, simulating water distribution with topographic considerations (e.g., in Kashkadarya's depressions, where lakes act as local reservoirs). Limitations involve data paucity beyond 2025 (drawn from 2015-2024 observations), yet projections remain sturdy owing to Monte Carlo (variance <10 %). Scopus examinations stress the imperative for hybrid frameworks (AI+RO) in dry areas: for instance, in Israel and Spain, such systems mitigate salinization hazards by 35–45 %, merging ANN with RO for anticipatory upkeep and power efficiency (ROI 3–5 years), paralleling the outlined approach.

This section promotes reproducibility, with the corresponding code made available in the GitHub repository.

RESULTS

Simulations executed in Python, leveraging TensorFlow and scikit-learn, illustrate the efficacy of the integrated AI-RO framework under the conditions prevalent in the Kashkadarya region. Within the baseline scenario, which assumes ongoing reliance on water from the Amu Darya (5,8 km^3/year), no deficit emerges; however, the Kushtepa scenario—projecting a diversion of 10–20 km^3/year, equivalent to 17–30 % of the Amu Darya's flow as anticipated for 2028—yields a deficit of 1,9 km^3, corroborated by SWAT models and data from Uzhydromet (average flow of 79 km^3/year, with a projected decline of 15–29 % for Uzbekistan when accounting for climatic influences). In the AI-RO scenario, the deficit diminishes to 0,6–0,8 km^3 through the processing of 1,8 km^3 of wastewater from the Sichankul and Achinsk lakes (combined reserves ~6 km^3, mineralization 3–6 g/L), achieving RO recovery rates of 70–85 % alongside AI-driven optimization that curtails consumption by 35–38 % (consistent with studies in Uzbekistan, where drip irrigation enhances water use efficiency by 35–103 %).

Cotton yields exhibit an increase of 10–15 % (from 2,5–3 t/ha in conventional practices to 2,8–3,5 t/ha under AI-RO), validated by AquaCrop models tailored to Uzbekistan, where AI-enhanced fertigation boosts yields by 13–19 % while conserving 50–60 % of water. Salinity levels are reduced by 40–50 % (from 3–6 g/L to <1 dS/m) via RO, mirroring outcomes in comparable systems for agricultural wastewater treatment (recovery 70–90 %, salinity abatement 80–95 %).

Table 1. Water balance projections (km^3/year)

Scenario	Amu Darya	Lakes (reprocessed)	Total	Deficit
Baseline	5,8	0,5	6,3	0
Kushtepa	3,9	0,5	4,4	1,9
AI-IO	3,9	1,8	5,7	0,6

Compensation through solar energy sources (20–40 %, at 2–4 kWh/m^3 for RO) mitigates costs, akin to solar-RO initiatives (return on investment spanning 3–5 years). These findings underscore the capacity for 1,8 km^3 of reuse, thereby attenuating the impacts of Kushtepa.

DISCUSSION

Analysis of Effectiveness

The findings obtained substantiate the efficacy of the integrated AI-RO system for managing drip irrigation in the Kashkadarya region, where modeling exercises reveal a reduction in water usage by 35–38 % alongside an increase in cotton yields by 10–15 %. This aligns with evidence from Scopus-indexed studies, indicating that in comparable arid environments, AI-based frameworks achieve prediction accuracies of 87–95 % for evapotranspiration, thereby mitigating errors in sparsely distributed sensor networks to 10–15 % through calibration of IoT-derived information. Nevertheless, the precision of AI applications is fundamentally contingent upon data quality; in networks with low sensor density (less than 0,5 per hectare), errors may escalate to 12–

15 %, akin to patterns observed in edge-computing AI models for agricultural settings, where insufficient data volumes contribute to overfitting phenomena. Such considerations necessitate the augmentation of IoT infrastructure to ensure resilient forecasting capabilities.(30,31,32,33)

Handling of RO brine (constituting 20–30 % of the processed volume, typical for treating brackish wastewater with total dissolved solids ranging from 2000–4000 mg/L) poses a significant challenge: concentrated brine exceeding 50 g/L in salinity demands disposal through methods like evaporation basins or subsurface injection to avert contamination of aquifers, as outlined in established protocols for RO brine management, wherein inadequate practices can elevate salinity hazards by 20–50 %. Incorporating solar power sources (yielding 20–40 % energy offset) serves to curtail operational expenditures (1,5-2,5 kWh/m^3), thereby rendering the system more environmentally viable.(34,35,36)

From a geopolitical perspective, decentralizing water supplies (via repurposing lake-derived wastewater) alleviates vulnerabilities associated with the Kushtepa diversion (withdrawing 10–20 km^3 annually), diminishing reliance on the Amu Darya by 20–30 %, albeit necessitating capital outlays: expenditures for AI-RO implementations approximate 100–200 USD per hectare (encompassing drip setup costs of 300–1200 USD per acre and supplementary AI components at 50–200 USD per acre), with a return on investment spanning 3-5 years under subsidized conditions. Parallels with Israeli paradigms (reutilizing 86 % of wastewater in farming, supported by 50–70 % subsidies on water technologies and reduced rates for agricultural users) affirm scalability: Israel attains water use efficiencies of 92–95 % through comparable commitments, emphasizing desalination and recycling strategies.(37,38,39)

Constraints encompass overlooked climatic fluctuations (with variability in runoff reaching 20-30 % due to drought episodes), suggesting the adoption of ensemble forecasting techniques for irrigation planning, as exemplified in NMME and NWP frameworks, where multimodel ensembles diminish uncertainty by 15–25 %, facilitating responsive resource governance.

CONCLUSIONS

The derived outcomes highlight the substantial potential of an integrated system based on artificial intelligence (AI) and reverse osmosis (RO) in addressing water scarcity issues in Uzbekistan's Kashkadarya region. Scenario modeling indicates that this system can avert an annual irrigation water deficit of up to 1,5 km^3, particularly amid geopolitical risks from the Kushtepa canal diversion of Amu Darya flow (projected reduction of 25–30 % by 2030). This is accomplished through resource allocation optimization: AI enables dynamic irrigation management, decreasing consumption by 35-38 % and boosting cotton yields by 10–15 %, while RO facilitates effective treatment of wastewater from artificial lakes Sichankul and Achinsk (total storage around 6 km^3), achieving recovery rates of 70–85 % and minimizing soil salinization (salinity reduction by 40–50 %).

In a broader context, the proposed approach enhances the resilience of agricultural systems in arid Central Asian zones, where climate change and anthropogenic pressures exacerbate water stress. It aligns with the UN Sustainable Development Goals (SDG 6 and SDG 13), offering a framework for transboundary resource governance that decentralizes sources, reduces Amu Darya dependency, and mitigates conflicts. Economic assessment reveals a return on investment within 3–5 years when incorporating solar energy to offset RO energy costs (1,5–2,5 kWh/m^3), rendering the technology feasible for small-scale farms (100–500 ha).

Recommendations encompass initiating pilot projects for AI-RO implementation in key Kashkadarya districts to validate empirically (with budgets of 100–200 USD/ha), fostering international dialogues on joint Amu Darya management (including Afghanistan for Kushtepa monitoring), and providing government subsidies for technologies (up to 50–70 %, akin to Israeli models). Future research should emphasize ensemble climate forecasts and system scaling for other basins, considering brine ecological risks and lake biodiversity.

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