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AI-DRIVEN STORMWATER HARVESTING, TREATMENT, AND REUSE IN HYPER-ARID COASTAL MANGYSTAU: CASE STUDY

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Abstract: This study evaluates the operational feasibility and socio-economic viability of harvesting, routing, and treating ephemeral stormwater runoff in the hyper-arid coastal region of Mangystau, Western Kazakhstan. The region faces severe water scarcity, relying on energy-intensive reverse osmosis desalination and vulnerable transboundary water supplies, while experiencing climate-induced flash floods. To address this challenge, a cyber-physical Smart Stormwater Management System was developed and simulated. The system integrates IoT edge sensing, a dual-layer Long Short-Term Memory network for runoff forecasting, Deep Q-Learning for automated first-flush gate control, and modular underground purification units. Results show that the system captures up to 82% of annual urban runoff, isolates 94% of initial pollutant loads, and supplies secondary water covering 24–30% of non-potable municipal demand. Energy consumption is reduced by over 85% compared with regional reverse osmosis desalination (0.55 vs. 4.20 kWh/m³), with a projected payback period of 5.2 years. The findings demonstrate the potential of AI-driven infrastructure to transform episodic stormwater into a valuable secondary water resource.

Keywords: artificial intelligence; stormwater harvesting; water reuse; hyper-arid regions; runoff prediction; reinforcement learning; water security.

Introduction.

The Mangystau Peninsula in Western Kazakhstan represents one of the most hydrologically stressed regions in Central Asia. Receiving an average annual precipitation of only 100-150mm, the territory possesses no permanent natural surface freshwater bodies. Urban centers like Aktau depend almost entirely on three high-risk water vectors: transboundary pipeline imports, seawater desalination, and deep aquifer extraction. Figure 1 illustrates the current water dependency of the Mangystau Peninsula and the hyper-arid paradox arising from the combination of low annual precipitation, intense ephemeral storms, unmanaged runoff, urban flooding, and contamination.

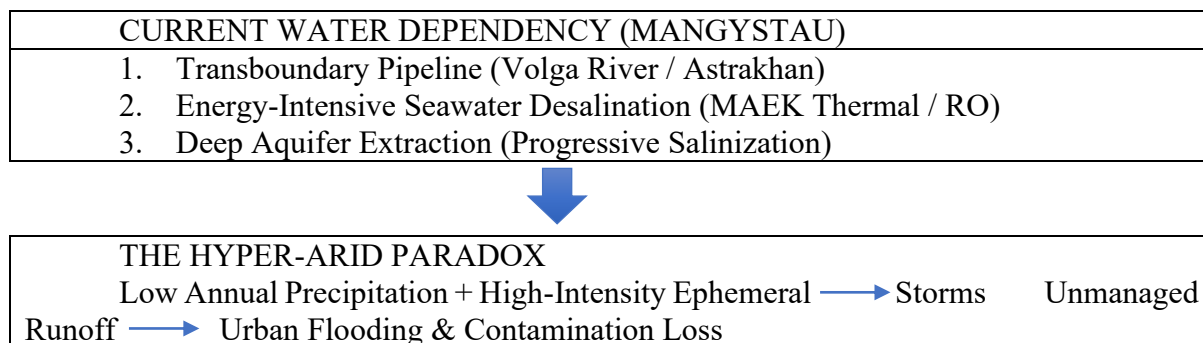


Figure 1 – Water Supply Dependency and the Hyper-Arid Stormwater Paradox of the Mangystau Peninsula

Transboundary Pipeline Imports: Surface water transported over 1,000 km via the Astrakhan–Mangyshlak pipeline from the Volga River, exposing the region to upstream geopolitical and ecological risks.

Seawater Desalination: Thermal and Reverse Osmosis (RO) plants (such as the MAEK complex) that supply the bulk of municipal water, operating at high operational expenditures 3.8-5.2 kWh/m³ and discharging hypersaline brine into Caspian coastal ecosystems [3, 4].

Deep Aquifer Extraction: Brackish groundwater reserves subject to accelerated depletion and rising mineralization levels [5].

Concurrently, regional climate projections indicate an increased frequency of short-duration, high-intensity storm events [6]. When sporadic precipitation occurs, the hyper-arid, heavily crusted soil and dense asphalt in Aktau prevent natural infiltration. The resulting runoff sweeps up urban pollutants-hydrocarbons, heavy metals, rubber particulates, and saline dust-causing localized flash flooding and asphalt erosion before discharging uncaptured into the Caspian Sea or inland salinized depressions (sor) [6, 7].

Desalination plants consume substantial electricity from a regional energy grid reliant on fossil fuels, contributing to high municipal water tariffs and greenhouse gas emissions [3, 8]. Meanwhile, millions of cubic meters of high-quality surface water are lost during short storm windows. Mismanaging this runoff causes recurring municipal losses through road surface destruction, foundation instability, and emergency drainage pumping [6, 9].

Research Questions & Core Thesis

This study addresses three central research questions:

1. What is the theoretical and harvestable surface water yield from ephemeral urban precipitation across Aktau's catchment zones?
2. Can an AI-driven control framework dynamically separate initial contaminated "first-flush" runoff from clean stormwater under hyper-arid field conditions?
3. What are the net energy, carbon, and financial savings of substituting desalinated water with harvested stormwater for non-potable urban applications?

We argue that integrating active cyber-physical control-combining predictive neural networks, real-time IoT water quality sensing, and automated gate actuation-can transform ephemeral flash floods into a reliable, low-carbon secondary water supply.

Literature Review

Urban stormwater harvesting and Low Impact Development (LID) techniques-such as bioswales, rain gardens, and permeable pavements-are widely established in temperate climate zones [10]. Research confirms that capturing stormwater mitigates peak flow volumes, recharges local water tables, and provides secondary non-potable water for irrigation and municipal cooling [10, 11]. Furthermore, advanced data-driven hydrological models, particularly Recurrent Neural Networks (RNNs), have shown high efficacy in predicting urban runoff hydrographs under complex weather patterns [12, 13].

The applicability of traditional, passive LID infrastructure in hyper-arid environments remains widely disputed [14]. Comparative studies demonstrate that passive bio-retention cells routinely fail in desert regions due to multi-month drought periods that kill vegetative layers, causing soils to harden and scour during sudden high-velocity storm events [14, 15]. Scholars also debate whether centralized surface retention basins or decentralized subterranean storage vaults offer the optimal trade-off between evaporation mitigation, structural footprints, and construction costs in densely built urban microdistricts [9, 14].

Existing literature lacks frameworks for active, real-time cyber-physical control customized for hyper-arid, coastal, and high-salinity urban environments [16]. Standard systems rarely integrate real-time water quality IoT telemetry with automated reinforcement learning (RL) gate routing to solve the severe "first-flush" contamination problem typical of hyper-arid urban runoff [17, 18].

Research Materials and Methods. Hydrological Catchment & Runoff Modeling.

The theoretical runoff potential across Aktau's urban footprint (35 km²) was quantified using a modified Rational Method integrated with regional Intensity-Duration-Frequency (IDF) curves

[6, 19]. The peak runoff flow rate was calculated using the modified Rational Method, as shown in Equation (1).

$$Q_p = 0.00278 * C_{comp} * I(T_r, t_c) * A \quad (1)$$

Where:

Q_p = Peak runoff flow rate (m^3/s)

C_{comp} = Composite runoff coefficient (0.72-0.84 for dense asphalt, concrete, and crusted vacant lots) [9]

$I(T_r, t_c)$ = Rainfall intensity (mm/hr) for a 5-year return period (T_r)

t_c = The time of concentration was calculated using the Kirpich equation, as shown in Equation (2) [19]:

$$t_c = 0.0195 * L^{0.77} * S^{-0.385} \quad (2)$$

A = Drainage catchment area (ha)

Cyber-Physical Framework Architecture

The proposed cyber-physical framework consists of three interconnected layers: edge sensing and IoT, AI-based predictive and decision control, and subterranean purification and storage, as illustrated in Figure 2.

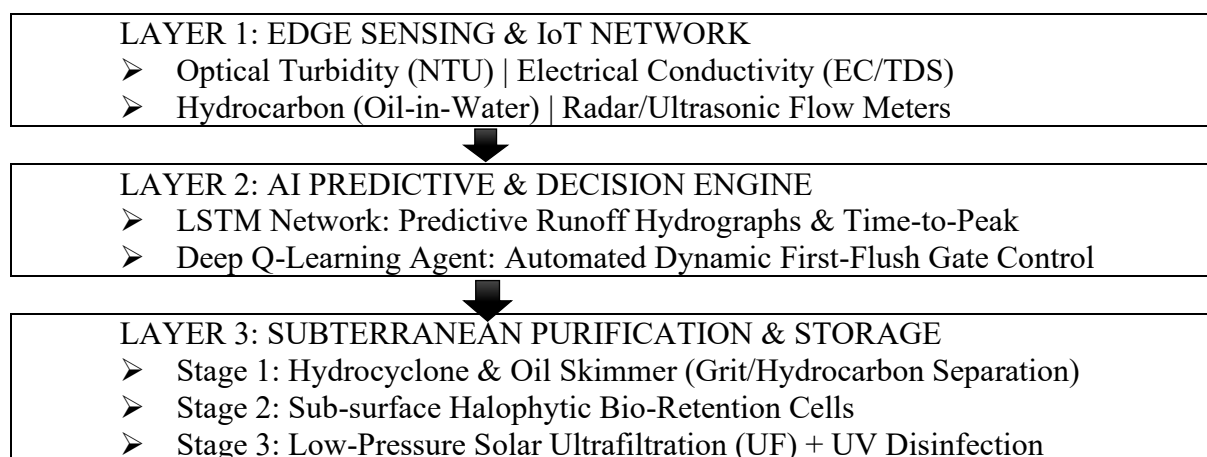


Figure 2. AI-Driven Cyber-Physical Stormwater Management System Architecture

Layer 1: IoT Edge Sensing Array

Solar-powered sensor nodes deployed across drainage channels, locally known as sayas transmit telemetry every 15 seconds via LoRaWAN [16, 20]: Optical Turbidity (NTU), Electrical Conductivity (EC/TDS), Hydrocarbon concentration (oil-in-water fluorescence probes), and Doppler flow velocity. To ensure data fidelity despite multi-month drought periods, optical lenses and fluorescence probes are integrated with automated mechanical wiper/air-blast self-cleaning mechanisms and scheduled zero-point auto-calibration protocols triggered prior to forecasted storm events to mitigate dust encrustation, sensor desiccation, and biofouling.

Layer 2: AI Control Engine

- **Runoff Forecasting (LSTM):** A dual-layer Long Short-Term Memory network processes satellite weather radar, micro-station rainfall intensity, and soil moisture index inputs to forecast incoming hydrographs 1-4 hours in advance [12, 13].

- **Dynamic First-Flush Routing (Deep Q-Learning):** A Deep Q-Learning (DQL) reinforcement learning agent evaluates real-time sensor streams to actuate electromechanical diversion gates at drainage junctions [18]. The agent isolates heavily contaminated initial runoff (15-20 min) from main storage vaults.

Layer 3: Subterranean Modular Purification

To prevent severe atmospheric evaporation ($>1,000$ mm/year in Mangystau), water is directed into subterranean modular geocellular vaults equipped with [14, 21]:

1. Hydrocyclone grit separators and passive oil-water skimmers [22].
2. Sub-surface bio-retention beds planted with indigenous halophytes (*Salsola*, *Tamarix*) for nutrient and heavy metal uptake [15, 23].
3. Solar-powered Low-Pressure Ultrafiltration (UF) and Ultraviolet (UV) disinfection units [24].

Techno-Economic & Energy-Water Nexus Formulation

Specific Energy Consumption (SEC) was calculated using the following equation, as shown in Equation (3):

$$SEC = \frac{E_{\text{pumping}} + E_{\text{treatment}}}{V_{\text{harvested}}} \quad (3)$$

where SEC is the specific energy consumption (kWh/m³), E_{pumping} is the energy required for pumping (kWh), $E_{\text{treatment}}$ is the energy required for water treatment (kWh), and $V_{\text{harvested}}$ is the volume of harvested water (m³) [3, 24].

Financial feasibility was assessed using the Amortized Payback Period (PB) model, as shown in Equation (4):

$$PB = \frac{\text{CapEx}_{\text{Initial}}}{\sum_{t=1}^N (\Delta C_{\text{water}} + C_{\text{flood_avoided}} - \text{OpEx}_t)} \quad (4)$$

Where ΔC_{water} represents savings from replacing desalinated water purchases, $C_{\text{flood_avoided}}$ accounts for avoided municipal road repairs, and OpEx_t covers routine system maintenance [3, 9].

Research Results. Harvestable Hydrological Yield

Simulations across Aktau's 35 km² urban core indicate that seasonal precipitation generates an average of 1.2-1.8 million m³ of surface runoff annually [6, 9]. A standard 1 km² microdistrict during a 25 mm/hr storm event lasting two hours produces approximately 18,500 m³ of harvestable water.

AI Routing & Pollution Isolation Performance

The Deep Q-Learning (DQL) agent achieved a 94% isolation rate for first-flush pollutant spikes (TDS $> 3,000$ mg/L, Turbidity > 150 NTU, Hydrocarbons > 5 mg/L) [18]. By bypassing only the initial 15% of heavily contaminated volume, the agent successfully harvested 82% of total storm volume at near-potable baseline quality [17, 18].

Energy Consumption and Carbon Offsets

- Specific Energy: $SEC_{\text{SSMS}} = 0.55$ kWh/m³ versus $SEC_{\text{RO}} = 4.20$ kWh/m³, yielding an 86.9% reduction in primary energy consumption [3, 24].
- Carbon Reduction: Mitigates carbon emissions by 3.2-3.9 kg CO₂e per cubic meter harvested, based on Western Kazakhstan's regional electricity grid emissions profile [8].

Economic Payback & Demand Offset

The harvested stormwater can partially substitute conventional water sources across several non-potable urban and industrial applications. Table 1 summarizes the proposed application sectors, required water quality standards, replaced water sources, and estimated non-potable demand offsets.

Table 1. Economic Payback and Non-Potable Demand Offset by Application Sector

Application Sector	Water Quality Standard	Replaced Water Source	Non-Potable Demand Offset
Urban Greening & Forestry [23]	Turbidity < 10 NTU,	RO Drinking Water / Trucked Water	100% of park irrigation

	Hydrocarbons < 0.5 mg/L		
Industrial & Construction [3]	TSS < 5 mg/L, Neutral pH	Potable Municipal Grid	100% of quarry/site dust suppression
Municipal Utility Services [10]	Primary Filtration + UV (<1 NTU)	Desalinated MAEK Supply	100% of street washing & fire reserves

- Overall Non-Potable Supply Offset: Harvested water replaces 24-30% of total municipal non-potable consumption across Aktau [9].

- Financial Payback: Incorporating avoided asphalt damage ($C_{\text{flood_avoided}}$) and displaced commercial water tariffs (1.2-1.8 USD/m³), the initial capital investment is fully recovered in 5.2 years [3, 9].

The results demonstrate that unmanaged urban stormwater in hyper-arid regions can be converted from an infrastructure hazard into a high-value secondary water source. The high operational accuracy of the DQL agent resolves the primary historical barrier to desert stormwater harvesting: extreme initial pollutant loads caused by accumulated dust and automotive residue [14, 17].

From an operational standpoint, maintaining the integrity of the IoT sensing layer during extended dry spells represents a critical prerequisite for accurate AI gate control. To prevent optical turbidity and hydrocarbon sensors from degrading due to dust accumulation, biofouling, and lens desiccation during multi-month droughts, the edge node design incorporates automated mechanical wipers, low-power air-blast actuators, and pre-storm zero-calibration routines, ensuring continuous measurement accuracy upon initial runoff arrival.

Substituting desalinated water with harvested stormwater generates multi-sector benefits across the regional nexus:

- Grid Relief: Reduces baseline electrical loads on regional thermal power plants during seasonal pumping surges [3, 8].

- Caspian Coastal Protection: Decreasing desalinated volume requirements directly reduces hypersaline brine discharge volumes into Caspian marine habitats [3, 4].

- Microclimate Regulation: Providing secondary water for urban green belts combats the Urban Heat Island (UHI) effect and stabilizes dusty topsoil, mitigating regional dust storm severity (shamal) [6, 23].

Conclusion

An AI-driven cyber-physical stormwater management system offers an effective solution to the hyper-arid flash-flood paradox in Mangystau. By combining real-time IoT edge sensing, predictive LSTM neural networks, automated DQL first-flush routing, and subterranean purification, the framework yields over 1.2 million m³ of clean secondary water annually while reducing specific energy consumption by 86.9% compared to reverse osmosis desalination.

Practical & Policy Recommendations:

For municipal stakeholders and regional planning bodies in Western Kazakhstan, we outline a three-stage implementation roadmap:

1. Pilot Phase: Construct an IoT-instrumented subterranean storage vault beneath a high-imperviousness sector in Aktau (e.g., Microdistrict 14 or 15) to calibrate hydrological sensors and algorithms under field conditions.

2. Regulatory Policy: Amend regional urban planning codes to require modular geocellular stormwater catchment blocks beneath new public parking structures and commercial developments.

3. Full Scale-Up: Establish a decentralized dual-water pipe distribution network across Aktau to feed urban greening and industrial construction zones without tapping drinking water supplies.

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ГИПЕРҚҰРҒАҚ ЖАҒАЛАУЛЫ МАҢҒЫСТАУ ӨңІРІНДЕ ЖАСАНДЫ ИНТЕЛЛЕКТ НЕГІЗІНДЕ НӨСЕРЛІК СУДЫ ЖИНАУ, ТАЗARTY ЖӘНЕ ҚАЙТА ПАЙДАЛАНУ: КЕЙСТІК ЗЕРТТЕУ

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Аңдатпа: Бұл зерттеуде Батыс Қазақстанның гиперқұрғақ жағалаулы Маңғыстау өңіріндегі қысқа мерзімді нөсерлік ағынды суларды жинаудың, бағыттаудың және тазартудың техникалық орындылығы мен әлеуметтік-экономикалық тиімділігі бағаланады. Өңірде су тапшылығының жоғары деңгейі байқалады: су тұщыту үшін энергияны көп қажет ететін кері осмос технологиясына және осал трансшекаралық су көздеріне тәуелділік қалыптасқан. Сонымен қатар, климаттың өзгеруіне байланысты нөсерлік тасқындар орын алуда. Осы мәселені шешу үшін кибер-физикалық Smart Stormwater Management System жүйесі әзірленіп, модельденді. Жүйе IoT негізіндегі шеткі датчиктерді, ағынды суды болжауға арналған екі қабатты Long Short-Term Memory желісін, алғашқы ластанған ағынды автоматты басқаруға арналған Deep Q-Learning алгоритмін және жерасты модульдік тазарту қондырғыларын біріктіреді. Нәтижелер жүйенің жылдық қалалық нөсерлік ағынның 82%-ына дейін жинайтынын, бастапқы ластаушы заттардың 94%-ын оқшаулайтынын және ауызсуға арналмаған коммуналдық қажеттіліктің 24–30%-ын өтей алатын қосымша су көзін қамтамасыз ететінін көрсетті. Энергия тұтыну өңірлік кері осмоспен салыстырғанда 85%-дан астамға төмендейді (0,55 және 4,20 кВт·сағ/м³), ал болжамды өтелу мерзімі 5,2 жылды құрайды. Зерттеу нәтижелері жасанды интеллектке негізделген инфрақұрылымның мерзімді нөсерлік суларды құнды қосалқы су ресурсына айналдыру әлеуетін көрсетеді.

Түйін сөздер: жасанды интеллект; нөсерлік суды жинау; суды қайта пайдалану; гиперқұрғақ өңірлер; ағынды суды болжау; күшейтілген оқыту; су қауіпсіздігі.

СБОР, ОЧИСТКА И ПОВТОРНОЕ ИСПОЛЬЗОВАНИЕ ЛИВНЕВЫХ ВОД НА ОСНОВЕ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА В ГИПЕРАРИДНОМ ПРИБРЕЖНОМ МАНГИСТАУ: КЕЙС-ИССЛЕДОВАНИЕ

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Аннотация: В данном исследовании оцениваются эксплуатационная осуществимость и социально-экономическая эффективность сбора, управления потоком и очистки кратковременных ливневых стоков в гипераридном прибрежном регионе Мангистау на западе Казахстана. Регион сталкивается с острой нехваткой воды, полагаясь на энергоёмкое опреснение морской воды методом обратного осмоса и уязвимые трансграничные источники

водоснабжения, одновременно подвергаясь климатически обусловленным ливневым паводкам. Для решения этой проблемы была разработана и смоделирована киберфизическая система интеллектуального управления ливневыми водами. Система объединяет периферийные датчики IoT, двухслойную сеть Long Short-Term Memory для прогнозирования стока, алгоритм Deep Q-Learning для автоматического управления затворами первичного стока и модульные подземные установки очистки. Результаты показывают, что система способна собирать до 82% годового городского ливневого стока, задерживать 94% начальной загрязняющей нагрузки и обеспечивать дополнительный источник воды, покрывающий 24–30% коммунального спроса на непитьевую воду. Энергопотребление снижается более чем на 85% по сравнению с региональным опреснением методом обратного осмоса (0,55 против 4,20 кВт·ч/м³), а прогнозируемый срок окупаемости составляет 5,2 года. Полученные результаты демонстрируют потенциал инфраструктуры на основе искусственного интеллекта для преобразования периодических ливневых стоков в ценный вторичный водный ресурс.

Ключевые слова: искусственный интеллект; сбор ливневых вод; повторное использование воды; гипераридные регионы; прогнозирование стока; обучение с подкреплением; водная безопасность.