



A Novel High-Resolution Water Resources Assessment Model (HyDRA version 1.0) for Industrial and Domestic Water Use: A regional application for the Gulf Cooperation Council (GCC) Countries and Jordan

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Abstract. Large-scale water models often generalize the methodology for developing regions by relying on coarse assumptions that fail to capture regional socioeconomic dynamics and the constraints of water-scarce systems, resulting in limited accuracy when evaluating water use across diverse economic and resource conditions. This gap is particularly evident in the Middle East, where data scarcity and underrepresentation hinder detailed assessments despite the region's critical importance in a water-dependent economy. To address this, this study develops HyDRA ("High-Resolution Water Resources Assessment Model") model, a model designed to improve the estimation of industrial and domestic water use through dynamic socioeconomic drivers and regionally available data. The model disaggregates industry into ten subsectors nearly covering all the industrial activities—electricity generation, petro-refining, chemical and petrochemical industries, cement, basic metals, food and beverage, paper and pulp, oil extraction, mining, and other manufacturing—each linked to distinct production indicators and corresponding water use intensities, alongside a domestically adaptive module that captures variations in per capita water use driven by demographic, economic, and infrastructure changes. Implemented at a fine spatial resolution of 3 arcseconds (~90 m), the model enables detailed, location-specific estimates of water withdrawal and consumption at both national and subnational scales. Its application to the GCC countries and Jordan over the period 1990–2025 provides a long-term reconstruction across hydro-economically contrasting systems, where the GCC represents one of the world's most concentrated hubs of water-intensive industrial activity, while Jordan reflects a structurally distinct yet equally water-scarce system. Together, these regions form a critical testbed for analyzing water economy dynamics under extreme scarcity. By explicitly resolving sectoral production structures and socioeconomic adaptation, the model advances beyond conventional top-down scaling approaches, improving cross-country comparability while preserving regional specificity. Although demonstrated for the GCC and Jordan, the model structure is transferable and can be extended to other regions, given appropriate socioeconomic inputs and harmonized statistical data.



1 1 Introduction

2 Water is a cornerstone of coupled hydrological and socio-economic systems, essential for the environment and
3 ecosystem integrity (Gleick, 2023; Kahil et al., 2025; Van Vliet et al., 2017; Wada & Bierkens, 2014; Zarei et al.,
4 2025). While water underpins agriculture, energy production, industry, and domestic use, its distribution is highly
5 uneven, with over 33% of the global population living in water scarce regions (Reynolds et al., 2007; Zhang et al.,
6 2024). Over the past century, global freshwater withdrawals have increased by approximately 600%, driven by
7 population growth, economic development, industrialization, and expanding urban areas (Boretti & Rosa, 2019; du
8 Plessis, 2023). An increase of 50–80% in global industrial and domestic water use is anticipated over the coming
9 three decades, driven by accelerating population growth, expanding urban areas, and broader socioeconomic
10 advancement (Flörke et al., 2018; Garrick et al., 2019; He et al., 2021; Ren et al., 2025). Understanding these
11 dynamics is therefore critical for developing strategies that reconcile human water needs in an increasingly water-
12 constrained world (Greve et al., 2018; Pokhrel et al., 2021; Rosa & Sangiorgio, 2025).

13 Large-scale hydrological models such as WaterGAP, PCR-GLOBWB, and H08 have been widely used to estimate
14 long-term sectoral water withdrawals and consumptions (Alcamo et al., 2003; Flörke et al., 2013; Hanasaki et al.,
15 2013; Müller Schmied et al., 2021; Wada et al., 2011). These models excel at producing consistent multi-decadal
16 reconstructions and projections at national or macro-regional scales. However, their general methodology and
17 associated assumptions introduce several limitations, including generalized globally applicable assumptions, coarse
18 spatial resolution leading to poor representation of urban and industrial areas, and the lack of water infrastructure
19 networks. For domestic water use, simplistic population-based scaling approaches introduce bias by assuming uniform
20 per capita use patterns that overlook regional socio-economic and household differences. Reconstruction of industrial
21 water use has relied largely on national-level regression approaches using variables such as population, gross domestic
22 product (GDP), and/or electricity production (Hanasaki et al., 2013; Wada et al., 2011). While suitable for large-
23 scale assessments, these approaches become less reliable when industrial structures and technologies evolve rapidly
24 in regions like the Middle East (Blanc et al., 2014; Nazemi & Wheeler, 2015). Moreover, Industrial water use is
25 often modeled as an aggregated category with limited sub-sectoral differentiation, reducing the ability to capture
26 evolving industrial sub-sectoral structures, particularly in rapidly developing and emerging economies (Flörke et al.,
27 2013; Wada & Bierkens, 2014). Collectively, these limitations introduce systematic biases when estimating
28 industrial and domestic water use across regions (Veldkamp et al., 2017)

29 Beyond large-scale hydrological models, a spectrum of alternative approaches seeks to capture finer-scale
30 heterogeneity and sector-specific dynamics to estimate water use, yet each introduces its own constraints by navigating
31 a fundamental trade-off between local accuracy and general applicability. Integrated Assessment Models (IAMs) such
32 as GCAM and IMAGE, for instance, are valuable for national-level policy and scenario analysis by incorporating
33 water, energy, and food nexus interactions (Bijl et al., 2018; Fujimori et al., 2017; Hejazi et al., 2014; Khan et al.,
34 2023). However, their applicability for smaller, water-scarce nations like those in the GCC and Jordan is
35 fundamentally limited by coarse spatial resolution, an aggregated representation of industrial subsectors, and static
36 assumptions regarding water infrastructure and household water use efficiency that fail to capture regional dynamics.



1 For instance, GCAM generally considers GCC countries as part of a single aggregated region, which leads to the
2 homogenization of highly heterogeneous national contexts. This regional aggregation masks critical differences in
3 water resource management, desalination dependency, industrial structure, and water policy, such as water tariffs
4 among countries such as Saudi Arabia, the UAE, Qatar, and Jordan. As a result, country-specific dynamics such as
5 rapid infrastructure expansion, shifts in desalination capacity, and targeted efficiency measures in industrial sectors
6 are not explicitly represented, leading to potential biases in water use estimation. Although some efforts have
7 attempted to disaggregate industrial water use into energy production, manufacturing, and cooling components, sub-
8 sector industrial representations remain simplified, similar to large-scale hydrological models.

9 Regional or country-specific models to estimate water use address many of these spatial and sectoral limitations by
10 providing the resolution needed to represent cities, multiple industrial subsectors, and the influence of local water
11 policies (House-Peters & Chang, 2011; Joseph et al., 2019; Ling et al., 2023; Su & Karthikeyan, 2023; Wang et al.,
12 2024). However, these models are often tailored to specific case studies, limiting their reproducibility and cross-
13 regional comparability. Moreover, many focus primarily on reproducing historical water use trends rather than
14 explicitly linking water use to evolving socio-economic drivers, technological change, and infrastructure development,
15 which constrains their applicability for forward-looking scenario analysis (Cazcarro et al., 2013; F. T. Avelino &
16 Dall'erba, 2020; M. Li et al., 2024). Furthermore, the existing literature remains limited and fragmented, with few
17 studies that systematically capture country-level heterogeneity. Most available applications are relatively simple in
18 structure, often relying on basic regression-based approaches with limited explanatory variables, or focusing on single-
19 city case studies or isolated single-country analyses without regional comparability. Within this body of work, socio-
20 economic and household characteristics such as income, household size, housing type, and education level are among
21 the most frequently studied drivers (Abushammala, 2017; Alazmi et al., 2024; Alfalah, 2021; Al-Maadid et al.,
22 2023; Almulhim & Abubakar, 2024; Almutaz et al., 2012; Fadlilmawla & Al-Otaibi, 2005; Freije et al., 2023;
23 Gharabaghi et al., 2019; Kalifa et al., 2021), while population growth and urbanization strongly influence domestic
24 water demand by reshaping consumption patterns and increasing pressure on centralized supply systems (Ahmed et
25 al., 2020; Al-Najjar et al., 2011; Fadlilmawla & Al-Otaibi, 2005; Kizhisseri et al., 2021; Long et al., 2022; Meng
26 & Wu, 2021), and climatic conditions further contribute to seasonal and spatial variability (Long et al., 2022; Meng
27 & Wu, 2021; Mohamed & Al-Mualla, 2010). Additional factors such as water tariffs, nationality, age structure, and
28 household behavior have also been incorporated to capture socio-economic and cultural heterogeneity (Alazmi et al.,
29 2024; Alfalah, 2021; Al-Maadid et al., 2023; Al-Najjar et al., 2011; Alqahtani et al., 2021; Fadlilmawla & Al-
30 Otaibi, 2005; Kalifa et al., 2021), although most studies remain country-specific with only limited extensions to
31 multi-country or regional scale (Ahmed et al., 2020; Long et al., 2022), resulting in key national scale dynamics
32 including sectoral differences in water use, rapid infrastructure expansion, and policy-driven efficiency improvements
33 remaining insufficiently represented and highlighting a clear need for more robust and transferable models,
34 particularly for water-scarce regions such as the Middle East.

35 In parallel, data-driven and hybrid approaches, including machine learning methods, have demonstrated potential for
36 capturing nonlinear relationships among socio-economic, climatic, and infrastructural drivers of water use (Bata et



1 al., 2020; G. Guo et al., 2018; Morain et al., 2024; Ulusoy et al., 2024), However, challenges related to
2 interpretability, data requirements, and transferability continue to limit their operational use (Babel et al., 2007;
3 Maußner et al., 2025; Shrestha et al., 2020).

4 To synthesize the landscape of existing water use modeling approaches, Table 1 provides a structured comparison of
5 large-scale hydrological models or GHMs, IAMs, regional/national, and AI/ML-based models. It summarizes their
6 sectoral coverage, spatial resolution, temporal scope, and methodological approach, enabling a clear assessment of
7 strengths, weaknesses, and methodological gaps. First, GHMs deliver consistent long-term data but are limited by
8 coarse resolution and aggregated sectoral assumptions, undermining local accuracy. Second, IAMs improve economic
9 integration and partial sub-sectoral details but remain constrained by regional aggregation and static assumptions
10 regarding domestic infrastructure. Third, regional and national models provide high spatial and sectoral fidelity yet
11 often lack transferability across regions and scenarios. Fourth, AI/ML approaches capture complex nonlinear
12 relationships but are hindered by data scarcity and weak integration with physically grounded water and socio-
13 economic processes. Collectively, these observations highlight a persistent gap; not a single model simultaneously
14 achieves a comprehensive industrial sub-sector disaggregation, dynamic socio-economic and infrastructural
15 representation, and cross-regional applicability at a high spatial resolution.

16 Water-scarce regions such as the GCC countries and Jordan provide a critical testbed for advancing water use
17 modeling. These regions combine rapid urbanization, evolving industrial structures, and strong reliance on non-
18 conventional water sources with significant data scarcity (Al-Zubari et al., 2017; Al-Zu'bi et al., 2025; Huang et al.,
19 2018; Wada et al., 2016). Including Jordan provides a strategic advantage, as a directly neighboring water-scarce
20 country, it shares climatic, hydrological, and social characteristics with the GCC, making it ideal for evaluating model
21 performance and regional water use dynamics for more stable countries. Unlike Egypt and Iraq, whose water systems
22 are strongly dependent on major perennial river systems, the GCC countries and Jordan rely heavily on groundwater,
23 desalination, and other non-conventional water resources. Countries such as Syria and Yemen were not considered
24 due to major limitations in consistent long-term water and socio-economic datasets associated with prolonged
25 instability and conflicts.

26 Building upon the development of the previous models (Table 1); The proposed methodology advances in several
27 aspects when estimating both industrial and domestic sectors in data-scarce regions of the GCC countries and Jordan.
28 Our approach combines high-resolution 3 arcseconds (~ 90 m) spatial assessment with explicit sub-sectoral and
29 infrastructure representation, enabling detailed characterization of water use dynamics across space and time. A key
30 feature of the model is the explicit disaggregation of industrial water use into ten subsectors, reflecting the
31 heterogeneous nature of industrial activity in the region, where each subsector was characterized by distinct production
32 processes, technologies, and water use intensities, thus covering the important industrial features. This coverage spans
33 nearly all industrial activities in the study region, allowing the model to detect structural changes in industrial activities
34 and development over time. In addition, water constraints were resolved at the plant location level, enhancing the
35 physical consistency and spatial precision of industrial use estimates. The domestic sector formulation represents an
36 advancement by explicitly incorporating infrastructural and built environment characteristics alongside socio-
37 economic and demographic drivers. In addition to population and economic indicators, the model accounts for urban



1 form, housing structure, and infrastructure-related efficiency dynamics, enabling domestic water use to be represented
2 as a transient function of both water use behavior and the underlying water network and urban systems. Overall, the
3 model is fully spatially explicit, sub-sectoral resolved, infrastructure represented, and cross-country comparable,
4 allowing it to capture structural transitions in water use across time and space within a unified model structure, giving
5 the flexibility to apply to other regions.

1 **Table 1: Comparison of global, regional, and national water use modelling studies with explicit sectoral depth, spatial resolution, temporal coverage, and methodological**
2 **approach.**

Study	Sectors	Spatial	Temporal	Methodology
Global Hydrological Models (GHMs)				
Alcamo et al.(2003)	Dom, Ind, Agr	Global (river basins)	1960–2000	Coupled water-use and hydrological balance modeling
Hanasaki et al. (2013)	Dom, Ind, Agr	Global, 0.5°	1900–2100	Physically based GHMs with abstraction modules
Wada et al. (2011)	Dom, Ind, Agr	Global, 0.5°	1960–2100	Socio-economic use functions coupled to GHMs
Flörke et al. (2013)	Dom, Ind (Manu, Elec), Agr	Global (country)	1950–2100	WaterGAP3 with sector-specific use drivers
Droppers et al. (2020)	Dom, Ind, Agr, Elec, Liv	Global	1980–2016	Human–Earth system modeling with managed water use
Global IAM-Based Models				
Bijl et al. (2018)	Mun, Ind (3 sub-sectors), Elec, Agr	Global, 0.5°	1971–2100	IAM-linked hydrology and macroeconomic allocation
Fujimori et al. (2017)	Ind (10 sub-sectors)	Global (17 regions)	2005–2100	CGE-based IAM with sector-resolved industrial water use
Hejazi et al. (2014)	Agr, Mun, Elec, Ind (aggregate)	Global (country)	2005–2100	GCAM IAM integrating economy–energy–land–water
Khan et al. (2023)	Dom, Ind, Agr	Global, 0.5°	2010–2100	Fully coupled IAM–land-use–hydrological model
Regional / National Models				
Hou et al.(2023)	Ind (enterprise-level)	China, 0.1°–0.25°	2000–2015	Bottom-up industrial scaling using firm statistics
Jiao et al. (2024)	Ind (selected sectors)	China (national)	2015–2060	Technology-rich IAM (IPAC-TechWater)
Wang et al. (2024)	Dom, (aggregate), Agr	Ind China (multi-scale)	2000–2030	Decomposition (Kaya–LMDI) + STIRPAT + climate



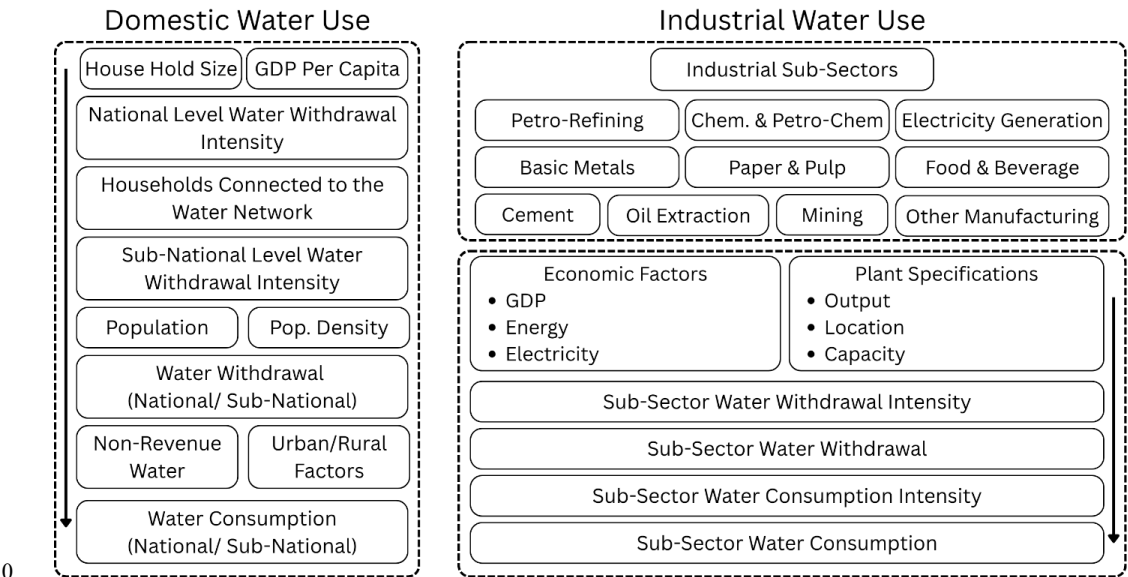


Alaznri et al. (2024)	Dom	Kuwait (national)	1995–2050	Spatial microsimulation constrained by demography
Almutaz et al. (2012)	Dom	Riyadh (Saudi)	1990–2031	Econometric use modeling
Kotagama et al (2017)	Dom	Oman	2005–2015	Econometric demand function modeling
Mohamed & Al-Mualla (2010)	Dom	Umm Al-Quwain, UAE	1980–2020	Constant Use Rate Model (IWR-MAIN)
Al-Zu'bi et al. (2026)	Dom, Ind (10 sub-sectors)	GCC & Jordan, 3"	1990–2025	Sectorally disaggregated socioeconomic model, coupling energy–economy structural drivers
"This Study"	AI / ML-Based Models			
Shu et al. (2024)	Dom, Ind, Agr, Eco	Tuojiang Basin	2000–2020	Hybrid ML (GPR, GA-BP) regression
Jiang et al. (2024)	Dom, Ind, Agr, Eco	China (province)	2005–2025	Hybrid optimization-enhanced neural networks
Yang et al. (2024)	Dom (urban)	Multi-city	2000–2022	GAN-based multivariate data fusion
Abushammal (2017)	Dom	Makkah (city)	1995–2014	ANN-based use forecasting
Ahmed et al. (2020)	Dom	UAE (national)	1990–2027	LSTM deep learning time-series modeling



1 **2 Model Framework**

2 This section presents the methodological framework developed to estimate water withdrawals and consumptions
3 across both industrial and domestic sectors. The framework integrates a regionally applicable, sector-specific
4 industrial module along with a domestic module capable of capturing sub-national water use. Together, these modules
5 provide a comprehensive, 3 arcseconds high-resolution representation of water use patterns. A model flowchart is
6 shown in Figure 1.
7 For the sake of simplicity and generality, the term water use is employed throughout this study to encompass both
8 water withdrawal and water consumption, as the underlying concept for modeling these quantities is largely
9 equivalent.



11 **Figure 1: A model overview showing the domestic and industrial model structure.**

12 **Table 2: A summary of the major datasets used in this study. The data comprises demographic, climatic, and socio-economic**
13 **inputs required for model parameterization. All variables were spatially and temporally harmonized to ensure consistency.**

Parameter	Source(s)
Population	CSB (2025), DOS (2025), FCSC (2025), GASTAT (2025), iGA (2025), NCSI (2025), PSA (2025), US Census Bureau (2025), and World Bank (2024).
Population Density	Schiavina et al. (2023).
Water Withdrawal	AQUASTAT (2026), DOS (2025), EuroStat (2026), FCSC (2025), GASTAT (2025), iGA (2025), and PSA (2025).



GDP	CSB (2025), DOS (2025), FCSC (2025), GASTAT (2025), iGA (2025), IMF (2026), NCSI (2025), PSA (2025), and World Bank (2026b).
Electricity	CSB (2025), DOS (2025), FCSC (2025), GASTAT (2025), IEA (2026), iGA (2025), NCSI (2025), and OWID (2026a).
Energy	OWID (2026b) and World Bank (2026a).
Household Size	CSB census (2005, 2011, 2021, DOS census (1994, 2004, 2015), GASTAT (2004, 2010, 2022), iGA census (1991, 2010, 2020, 2020), NCSI census (1993, 2003, 2010, 2020), PSA census (1986, 1997, 2004, 2010, 2020).
% of Houses Connected to the Water Network	CSB census (2005, 2011, 2021), DOS census (1994, 2004, 2015), GASTAT (2004, 2010, 2022), iGA census (1991, 2010, 2020), NCSI census (1993, 2003, 2010, 2020), and PSA census (1986, 1997, 2004, 2010, 2020).
Non-Revenue Water	Al-Bulushi et al. (2018), Ali et al. (2024), Al-Khalid et al. (2013), Alkhanbashi & Al Shuaili (2026), DOS census (1994, 2004, 2015), GRC (2020), NCSI census (1993, 2003, 2010, 2020), PSA census (1986, 1997, 2004, 2010, 2020, 2020), UN-WLC (2025).
Consumption Factor	Hejazi et al. (2013), World Bank (2026b).

2.1 Industrial Water Use

Industrial water withdrawal has long been associated with macroeconomic development, energy use, and evolving technological efficiencies. Gross domestic product (GDP) is commonly used to represent the overall scale of economic and industrial activity (Alcamo et al., 2007; Flörke et al., 2013; Hanasaki et al., 2013; Oki & Kanae, 2006; Wada et al., 2011). In addition, electricity generation per capita serves as a proxy for industrial energy demand, and has been shown to exhibit a strong empirical relationship with industrial water withdrawal (Alcamo et al., 2007; Flörke et al., 2013; Shen YanJun et al., 2008). Empirical assessments have also demonstrated a strong relationship between industrial water withdrawals and energy intensity, defined as energy use per unit of economic output (Hanasaki et al., 2013).

Building on these insights, our model represents industrial water use through a bottom-up structure that distinguishes ten key industrial sub-sectors: electricity generation, petro-refining, chemical and petrochemical industries, cement, basic metals, food and beverage, paper and pulp, oil extraction, mining, and other manufacturing. These sub-sectors capture the dominant contributors to industrial production and water use across most economies. Industrial water withdrawal is therefore estimated as a sum of the product of sub-sectoral production output and their respective water withdrawal intensity.

Water withdrawal $WW_{c,s,t}$ for country c , sub-sector s , and year t is calculated as:

$$WW_{c,s,t} = P_{c,s,t} \times WWI_{c,s,t} \quad (1)$$

where $P_{c,s,t}$ denotes production output, and $WWI_{c,s,t}$ represents water withdrawal intensity.

Unlike conventional models (Alcamo et al., 2007; Flörke et al., 2013; Hanasaki et al., 2013; Wada et al., 2011), which rely on explanatory variables to directly estimate industrial water use, this study utilizes these factors to characterize and quantify temporal efficiency gains across individual industrial subsectors:

$$WWI_{c,s,t} = WWI_{c,s,t_0} \times TEF_{c,s,t} \quad (2)$$



2

1

3 Here, $WWI_{c,s,t}$ is the water use intensity, while WWI_{c,s,t_0} is the baseline intensity at the reference year t_0 . For this
4 study, we are taking 2020 as a reference year. Temporal variations are governed by the techno-economic factor
5 $TEF_{c,s,t}$, which captures changes in economic scale and energy-system efficiency.

6 The TEF is formulated as a dimensionless scaling term:

8
$$TEF_{c,t} = \frac{1}{3} \left(\left(\frac{GDP_{c,t_0}}{GDP_{c,t}} \right)^{0.5} + \frac{Electricity_{cap,c,t_0}}{Electricity_{cap,c,t}} + EI \right) \quad (3)$$

7

9 In this formulation, GDP, per-capita electricity, and energy intensity are designed to exhibit a saturating, plateau-like
10 response over time. Specifically, the 0.5 exponent applied to the GDP ratio reflects diminishing marginal
11 improvements in industrial water use efficiency with increasing economic output. As economies mature, structural
12 and technological gains progressively saturate, limiting further reductions in water use intensity. The sublinear
13 transformation, therefore, moderates the influence of GDP, aligning its temporal response with the plateau-like
14 behavior observed in the per capita electricity and energy intensity.

15 Energy intensity is defined as:

16
$$EI_{c,t} = \frac{\left(\frac{Energy_{cap,c,t}}{GDP_{cap,c,t}} \right)}{\left(\frac{Energy_{cap,c,t_0}}{GDP_{cap,c,t_0}} \right)} \quad (4)$$

17 TEF captures the sensitivity of industrial water use intensity to large increases in economic output, technological
18 adjustments, and efficiency changes, while retaining responsiveness to early-stage growth and structural transitions.
19 By combining these three components, TEF provides a tractable value for representing the major socio-economic and
20 energy-related drivers of industrial efficiency improvements in regions lacking detailed process-level data.

21 Industrial water consumption $WC_{c,s,t}$ is calculated independently from withdrawal:

23
$$WC_{c,s,t} = P_{c,s,t} \times WCI_{c,s,t} \quad (4)$$

22

24 where $P_{c,s,t}$ denotes production output for the country c , sub-sector s , and year t , and $WCI_{c,s,t}$ represents water
25 consumption intensity.

26 Intensities are derived from a structured synthesis of national statistical datasets, industrial and energy sector reports,
27 corporate sustainability disclosures, and sector-specific technical literature, as shown in Table 2 and the various
28 upcoming industrial sub-sectors. The temporal evolution of these intensities was captured using the techno-economic
29 factor (TEF) (Eq. 3), which accounts for changes in economic scale, energy use, and efficiency improvements over
30 time for all the subsectors. For clarity, subsector-specific baseline withdrawal and consumption intensities are
31 provided in individual tables within each subsector section. Unless otherwise specified, water use intensities are
32 calculated as the ratio of water use to the corresponding sectoral or subsectoral production output. Water use is then
33 allocated among individual plants in proportion to their production capacities, unless an alternative allocation
34 approach is explicitly stated.



1 Table 3: Summary of industrial water use intensities across all industrial subsectors included in this study. Refer to the corresponding subsections for detailed descriptions
 2 of the derivation methods and underlying assumptions for each subsector.

Sub-Sector	WWI	WCI	Cooling Intensity/ Saline Water Intensity	Unit	Reference
Electricity Generation	Natural gas-Once through cooling	-	0.38	43	Macknick et al. (2012).
	Natural gas-Cooling towers	0.97	0.78	-	
	Natural gas- Dry	0.008	0.008	m ³ /MWh	
	Nuclear- Once through	-	1.02	m ³ /MWh	
	Nuclear- Cooling towers	4.17	2.54	m ³ /MWh	
Petro-Refining	Solar / Wind	0.00	0.00	-	Assumed zero due to the low water use for cleaning compared to other processes (Jones & Olsson, 2017).
	Light-Medium Oil	1-1.9	0.53-1.38	m ³ water/ m ³ oil	
Chemicals & Petro-Chemicals	Medium-Heavy oil	2.24-3.47	NA	m ³ water/ m ³ oil	LyondellBasel (2020, 2021, 2022, 2023), PIC (2014), QAPCO (2023), SABIC (2022).
	Pulp Production ≤ 10%	4.15-10.22	1.5	m ³ water/ tonne	
Paper and Pulp	Pulp Production > 10%	8.28-24.41	NA	m ³ water/ tonne	EuroStat, (2026), FAOSTAT (2025).
	Basic Metals Manufacturing	12.5-44.2	4	m ³ water/ tonne	
Food & Beverage	1-17	NA	-	m ³ water/ \$ Value Added	EuroStat (2026), EuroStat (2026), KAPSARC (2026), MAADEN (2024), Tong et al. (2018).



1

Cement Manufacturing		0.216-0.287	0.163-0.203	-	m ³ water/ tonne production	Buzzi Unicem (2021), CRH plc (2023), InterCement (2022), LafargeHolcim (2022).
Oil Extraction		1.26 - 3.36+	0 – 2.49+	-	m ³ water / m ³ oil	Derived using mass balance.
Mining	Ore mining	0.435-4.115	0.01-0.836	-	m ³ water/ tonne	Islam et al. (2025).
Mining	Potash (Dead Sea case)	4.83	3.14	42	m ³ water/ tonne	APC (2021, 2022).



1

2 2.1.1 Electricity Generation

3 Electricity Generation is one of the biggest water users (Lohrmann et al., 2022), and requires substantial volumes of
4 water, primarily for cooling and auxiliary processes (IEA, 2016; Terrapon-Pfaff et al., 2020). While only a fraction
5 of this water is consumed through evaporation or incorporation into products (Skinner et al., 2025). An accurate
6 estimation of both water withdrawals and consumptive use is critical for all nations' security. Recent studies further
7 show that shifts in the electricity mix, stricter thermal discharge regulations, and the adoption of recirculating, hybrid,
8 and dry cooling systems have substantially reduced water withdrawal intensities per unit of electricity produced (Byers
9 et al., 2014; Lohrmann et al., 2019; Skinner et al., 2025). This electricity-generation water use model captures these
10 dynamics across all major technologies, incorporating recent data for more efficient natural gas combined-cycle units,
11 renewable-linked thermal plants, and other emerging technologies.

12 The model distinguishes power plants based on their fuel type and cooling system configuration (e.g., once-through,
13 wet cooling towers, recirculating ponds, or hybrid/dry cooling). Water withdrawal and consumption intensities per
14 MWh were obtained from Macknick et al. (2012), while plant capacities were sourced from Byers et al. (2018).
15 Cooling system types for each plant were verified using Google Earth Engine (Gorelick et al., 2017). Electricity
16 generation at the plant level EG_i was not always directly reported and was therefore estimated by allocating total
17 electricity generation proportionally according to installed plant capacities. This capacity-weighted allocation assumes
18 that generation is distributed among plants in proportion to their relative capacities. Plant-specific water use was then
19 calculated as

$$20 \quad EGWU = EG_i \times WUI_i(CS_i, PT_i) \quad (5)$$

21

22 where $EGWU$ denotes electricity generation water use, EG_i is the electricity generated by plant i , and WUI_i represents
23 the water use intensity associated with plant i as a function of its cooling system (CS_i) and plant type (PT_i). This
24 model enables a detailed, technology-specific representation of water use in the electricity sector and reflects the
25 influence of evolving cooling technologies and changes in the electricity fuel mix on overall sectoral water use.

26 2.1.2 Petro-Refining

27 The petro-refining subsector is an intensive industrial user of freshwater, primarily used in process operations such as
28 distillation, heat exchange, and cooling (Ali & Kumar, 2017; Hashemi et al., 2024; Sun et al., 2018). The analysis
29 distinguishes between different crude oil types, "light-to-medium" and "medium-to-heavy" oil, allowing each country
30 to have a tailored water withdrawal intensity reflective of its dominant crude profile, as shown in Table 3. Medium-
31 to-heavy crude oils had higher intensities reflecting the greater processing complexity associated with heavier crude
32 fractions, which typically require more extensive thermal processing, separation, and cooling operations.

33 For this study, median values of the reported ranges were adopted as representative intensities, for light-to-medium
34 crude oil, which is dominant in the area of study (Arafin et al., 2012; Baniasad et al., 2023). We used 1.5 m³ water



per m³ oil for medium-to-heavy crude, while average values of 0.96 m³ water per m³ oil and 40 were assigned for water consumption and cooling intensities, respectively, while the crude throughput data was obtained from KAPSARC (2022).

2.1.3 Chemicals & Petrochemicals Manufacturing

Building upon the assessment of water use in the petro-refining sector, the chemicals and petrochemicals subsector represents another cornerstone of industrial water use, driven by diverse production processes ranging from basic chemicals and fertilizers to polymers and specialty products (Hansen et al., 2018). While petro-refining primarily relies on water for thermal operations and cooling, chemical manufacturing requires water not only for heat management but also as a process medium in reactions, separations, and product conditioning (Ellis et al.; 2001). As shown in Table 3, Plant-level water withdrawal and consumption data from manufacturer reports were compiled from various sources to derive water use intensities (m³ per tonne of product). The median withdrawal and consumption intensities were 3.2 m³ per tonne and 1.6 m³ per tonne, respectively. These intensities provide basis for estimating annual water use in the chemicals and petrochemicals sector and align with the estimate from Hansen et al. (2018). For cooling purposes, this subsector withdraws substantial volumes of water; however, reported data remain limited, with SABIC (2022) reporting an estimated 80 m³ per tonne of product based on its own operations, while production data was obtained from GPCA (2015, 2017, 2022).

2.1.4 Paper & Pulp Manufacturing

The pulp and paper (P&P) industry is a major consumer of freshwater and generates substantial wastewater due to its large-scale operations and complex production processes (Kamali & Khodaparast, 2015). Freshwater use varies with raw material type (virgin versus recycled fibers), production process (mechanical, chemical, or combined), and product grade (newsprint, packaging paper, tissue, etc.), with recycled fiber-based mills generally consuming less water than virgin fiber mills (Atimtay & Sikdar, 2011). Technological improvements, including water recovery, recycling, and implementation of best available techniques (BAT), have significantly reduced water consumption over time (Esmaeeli & Sarrafzadeh, 2023).

Countries with pulp production less than 10% of the total output show only minor variations in water withdrawal. Across these countries, the interquartile range was approximately 4.52–8.81 m³ per tonne, with a median value of 7.62 m³ per tonne, consistent with previous studies (Esmaeeli & Sarrafzadeh, 2023; Olejnik, 2011) as further clarified in S1. While consumption intensity in the P&P industry is rarely reported, it will be considered only as the water evaporated which would account for 1–1.5 m³ per tonne (Olejnik, 2011). Production amounts were taken from FAOSTAT (2025).



1 2.1.5 Basic Metals Manufacturing

2 Basic metal manufacturing is inherently among the most water intensive sectors in industry, owing to the large
3 volumes of input materials, high energy and cooling uses, and the requirement for ore processing, smelting, refining,
4 and casting stages (Atimtay & Sikdar, 2011; Colla et al., 2017; Sharma et al., 2025). The mean and median water
5 withdrawal intensities were calculated using data from EuroStat (2026) and metal production statistics from
6 KAPSARC (2026), considering country level averages for the period 2015–2020. The results yielded an average of
7 32.6 m³/tonne and a median of 24.8 m³/tonne, which align with the upper range reported in previous studies on the
8 steel industry, where water withdrawal intensities typically range from 17.4 to 28.6 m³/tonne (Suvio et al., 2012; Tong
9 et al., 2018; World Steel, 2015). This suggests that many metals, not just steel, exhibit relatively comparable water
10 use intensities.

11 Data on water use for metals other than steel are limited, even at the company and producer level. Many producers
12 report only total water withdrawals or seawater intake, without specifying the portion that is desalinated or directly
13 associated with individual metal production. This lack of detail makes it infeasible to calculate metal-specific water
14 withdrawal intensities with confidence. Consequently, the sectoral WWI presented here should be interpreted as an
15 aggregate average across all basic metals, with steel likely dominating the total volume. Nonetheless, this average
16 remains meaningful, while individual metals undergo different processing steps, the reported water intensities of non-
17 steel metals are generally of the same order of magnitude, supporting the representativeness of the derived sector-
18 level value. In addition, seawater withdrawals for cooling purposes have been estimated from various reports, yielding
19 an average of ~70 m³/tonne (EGA, 2023; MAADEN, 2024). For consistency and comparability, this cooling water
20 intensity was applied uniformly across all basic metals in this study, as for consumption, it was estimated to be 4
21 m³/tonne (Chengkang et al., 2011; Tong et al., 2018)

22 2.1.6 Food & Beverage Manufacturing

23 Water use in the food and beverage (F&B) subsector extends beyond factory operations. The freshwater embedded in
24 processing and supply chains moves with trade, income levels, and dietary habits (Frontuto et al., 2025; Vanham et
25 al., 2017). In contrast, countries with plentiful freshwater may have higher water use per unit of output but face lower
26 immediate stress on local resources (Garnier et al., 2023). Water Withdrawal from Eurostat was divided by the value
27 added from the food and beverage sector from the GLORIA MRIO dataset (Lenzen et al., 2017, 2022). Then, a
28 relation was constructed between countries' F&B water withdrawal intensity and electricity per capita to estimate the
29 intensity for countries with missing values. The relation between withdrawal intensity and electricity per capita is
30 clarified in S2. WWI ranged from 1 – 17 m³/ \$ value added. Consumption intensity data were unavailable; therefore,
31 it was assumed that approximately 42% of total water withdrawals are effectively consumed, based on average
32 consumption-to-withdrawal ratios of the overall withdrawal industrial sub-sectors. The water use was distributed
33 across industrial areas in proportion to their spatial extent, such that larger industrial areas were assigned a
34 correspondingly greater share of total water use



2.1.7 Cement Manufacturing

Although cement manufacturing is mainly dry, water is still used for cooling, dust suppression, and equipment maintenance. Recent improvements, such as water recycling and closed-loop cooling systems, have contributed in reducing freshwater use while maintaining production efficiency (Khafajah et al., 2026). Intensities for cement water use were collected from companies' reports, as shown in Table 3. The median values were adopted to represent the sector, resulting in a water withdrawal intensity (WWI) of 0.279 m³/tonne and a water consumption intensity (WCI) of 0.163 m³/tonne. Production data was obtained from USGS (1996, 2000, 2005, 2010, 2015, 2020, 2025).

2.1.8 Oil Extraction

Being concentrated in specific countries, oil production can generate disproportionately high local water use, exacerbating stress on already scarce freshwater resources, similar to the GCC case (Ali & Kumar, 2017; Meißner, 2021; Miao, 2025; Nath et al., 2023). Oil production has grown substantially in the region of study over the recent decades, contributing significantly to industrial water use (Energy Institute, 2025). Expansion has been accompanied by substantial water requirements associated with drilling operations, cooling systems, enhanced recovery techniques, and pressure management. The model is based on standard reservoir material balance under waterflooding conditions with long-term voidage replacement equilibrium (VRR ≈ 1) (Dake, 1983; Lake et al., 2014). Produced fluids at reservoir conditions are expressed as:

$$V_{\text{prod, res}} = Q_o B_o + Q_w B_w \quad (6)$$

where Q_o and Q_w are the surface oil and produced water production rates, and B_o and B_w are the oil and water formation volume factors, respectively. Under voidage replacement conditions, the injected reservoir volume equals the produced reservoir volume:

$$V_{\text{inj, res}} = V_{\text{prod, res}} \quad (7)$$

The corresponding surface injection requirement is:

$$V_{\text{inj, surf}} = \frac{V_{\text{inj, res}}}{B_w} = Q_o \left(\frac{B_o}{B_w} + \text{WOR} \right) \quad (8)$$

where $\text{WOR} = \frac{Q_w}{Q_o}$ represents the produced water–oil ratio (Veil et al., 2004), increasing with reservoir maturity in waterflooded systems.

Produced water is partially recycled and reinjected into the system. The recycling efficiency η is defined as the fraction of produced water that is treated and reused:

$$V_{\text{recycled}} = \eta \cdot Q_w = \eta \cdot \text{WOR} \cdot Q_o \quad (9)$$



1 Within a consistent system boundary, the external water withdrawal is defined as the amount of water required from
2 outside sources (e.g., seawater, freshwater, or desalinated water) to satisfy the remaining injection demand not covered
3 by recycling:

$$W_{\text{withdrawal}} = V_{\text{inj,surf}} - V_{\text{recycled}} \quad (10)$$

$$W_{\text{withdrawal}} = Q_o \left(\frac{B_o}{B_w} + \text{WOR}(1 - \eta) \right) \quad (11)$$

5
7 This represents the gross external water input to the oil production system.

8 The water consumption is defined as the irreversibly lost fraction of water from the produced-water cycle due to
9 surface handling inefficiencies. A surface loss parameter α is introduced to represent losses such as evaporation,
10 sludge disposal, and treatment inefficiencies. Consumption is therefore defined as losses from the produced-water
11 stream only:

$$W_{\text{consumption}} = Q_o \cdot \text{WOR}[(1 - \eta) + \alpha\eta] \quad (12)$$

12
14 This formulation ensures a consistent system boundary in which withdrawal represents external water demand, while
15 consumption represents irreversible losses from the produced-water recycling loop.

16 The model assumes undersaturated reservoir conditions with no gas phase formation, consistent with classical
17 waterflooding assumptions from Dake (1983). Gas liberation and formation volume factor variations associated with
18 gas phases are neglected. The results represent long-term average steady-state behavior under sustained waterflood
19 operations rather than transient production dynamics.

20 As shown in Table 4, the parameter values were selected to represent typical conditions encountered in oil extraction
21 operations while maintaining consistency with ranges reported in the literature. An average oil formation volume
22 factor of $B_o = 1.3$ was adopted as a representative mid-range value within the reported interval of 1.01–1.60.
23 Similarly, the water formation volume factor was taken as $B_w = 1.03$, representing a central value within commonly
24 reported ranges. A water recycling efficiency of $\eta = 0.71$ was used based on Kassab et al. (2021), while a surface
25 water loss factor of $\alpha = 0.08$ was adopted following estimates by Veil et al. (2004). The water–oil ratio (WOR) shows
26 significant variability across reservoirs due to differences in field maturity, operational practices, and regional
27 conditions, with reported values spanning from 0.01–1.50 in several regional studies to average global estimates
28 approaching 4 and higher (Al Dhaif et al., 2021; Dawoud et al., 2024). To capture this variability while preserving
29 a representative regional-scale assumption, a WOR value of 2 was selected. Under these combined conditions, the
30 resulting withdrawal intensity was estimated at 1.96 m³ of water per m³ of oil produced, falling within the higher end
31 of literature-reported ranges and aligning with estimates for water-intensive production systems (Goodwin et al.,
32 2012). The corresponding consumption intensity was estimated at 0.83 m³/m³, providing a physically consistent and
33 representative basis for regional-scale water-use estimation. Oil field locations were obtained from the GEM (2026)
34 dataset. Annual oil production was allocated to individual onshore and offshore fields according to their reported
35 production capacities. Field capacities were assumed to remain constant throughout the study period due to the limited
36 availability of time-varying field-level production data. The estimated shares of national oil production originating



1 from onshore fields were 62.9% for Saudi Arabia, 30.7% for Qatar, 100.0% for Oman, 50.8% for the United Arab
 2 Emirates, 91.7% for Kuwait, and 20.4% for Bahrain. Offshore fields were excluded from the water-use assessment.
 3 National oil extraction volumes were obtained from KAPSARC (2026b).

4 **Table 4: Summary of key reservoir fluid properties and water management parameters.**

Symbol	Category	Range	Reference
B_o	Dead / Heavy Oil	1.00–1.05	McCain (1990, 1991)
	Ordinary Black Oil	1.05–1.60	
	Volatile Oil	1.60–5.00+	
B_w		1.00–1.06	
WOR		0-20+	Al Dhaif et al. (2021), Dawoud et al. (2024), Li et al. (2023)
η		0.71	Kassab et al. (2021)
α		0.08	Veil et al. (2004)

5
 6 For oil production, although technological advancements in extraction and drilling techniques have improved
 7 operational efficiency, these gains are often counterbalanced by reservoir aging effects, including declining well
 8 productivity and increasing water cut in mature fields, which tend to raise water requirements over time (Andersen
 9 et al., 2022). As these opposing processes can offset each other, resulting in no clear or stable net technological trend
 10 in water-use intensity, TEF-based adjustments were not considered. Instead, fixed coefficients provide a more robust
 11 and transparent representation of water use dynamics.

12

13 **2.1.9 Mining**

14 Although mining typically accounts for only 2–4.5% of national water withdrawals, its impact can be
 15 disproportionately large at regional and local scales—particularly in countries like Jordan, which is among the top 5
 16 global producers of phosphate and potash, and Saudi Arabia, which ranks in the top 10 for phosphate (Islam et al.,
 17 2025; Meißner, 2021). Mining water intensity values used in this study were derived from Islam et al. (2025) with
 18 average withdrawal and consumption intensities of 2.14 m³/tonne and 0.77 m³/tonne; However, potash extraction was
 19 treated as a unique case in Jordan. Potash production in Jordan relies on evaporating the Dead Sea water rather than
 20 conventional mining techniques. Accordingly, company-reported values were employed, yielding an estimated
 21 freshwater withdrawal and consumption intensity of 4.83 and 3.14 m³ per tonne respectively, while Dead Sea water
 22 withdrawal was estimated at 42 m³ per tonne (APC, 2022). The substantial difference is mainly driven by potash
 23 production processes, which require extracting large volumes of saline brine from the Dead Sea, while freshwater is
 24 used only for supporting auxiliary operations, leading to considerably lower overall water intensities. Except for
 25 Potash production in Jordan, mining was located using Maus et al. (2020) dataset, water use was distributed across



mining areas in proportion to their spatial extent, such that larger mining areas were assigned a correspondingly greater share of total water use, while mining production was compiled from KAPSARC (2025) and potash production was compiled from APC (1999, 2002, 2007, 2011, 2016, 2025) annual reports .

2.1.10 Other Manufacturing

To account for non-explicitly modeled industrial activities, an aggregated category termed other manufacturing was introduced. In the regional context, the unmodeled share mainly reflects dispersed and less systematically reported activities such as construction related operations, automotive and transport related industries (including vehicle assembly, maintenance, and large-scale washing facilities), textile and garment production where present (particularly dyeing, washing, and finishing processes), electronics and light manufacturing assembly, small metal workshops and surface treatment activities, as well as other small-scale or fragmented manufacturing operations that are typically embedded within broader national “manufacturing” statistics or not explicitly reported in sub-sector water withdrawal datasets.

Given the lack of consistent disaggregation for these activities, their combined water use was approximated as a fixed proportion of 5% of the total modeled industrial freshwater withdrawals, excluding electricity generation due to its distinct water use characteristics and separate representation within the model. This residual factor is therefore intended to close the industrial water balance by capturing unaccounted dispersed industrial demand rather than representing a directly observed or independently calibrated parameter. This parameter should therefore be interpreted as an approximation rather than an empirically derived quantity. As for consumption, it was also assumed to be 42% following the average consumption-to-withdrawal ratios of the other subsectors. And the water was distributed based on the industrial areas’ sizes.

2.2 Domestic Water Use

2.2.1 Domestic Water Use Formulation

Building on insights from previous studies, socioeconomic, demographic, and infrastructural factors were identified as key drivers of domestic water use. And following the formulation of global water use assessments similar to Flörke et al. (2013), Hanasaki et al. (2013), and Wada et al. (2011). The modeling approach progressed by selecting variables that are both regionally relevant and suitable for projections. Specifically, GDP per capita was used as a proxy for household income, household size to capture demographic influences, and the percentage of houses connected to the main water network (HCN%) to present the ease of access to potable water. In addition to the city’s urban–rural classifications, the model also incorporates a factor that has not received attention in previous studies, which is the percentage of non-revenue water to better account for actual water consumption patterns.

The domestic water withdrawal data were compiled from official governmental sources for each country within the study region. The other parameters were further corroborated using national publications and global datasets to ensure consistency.



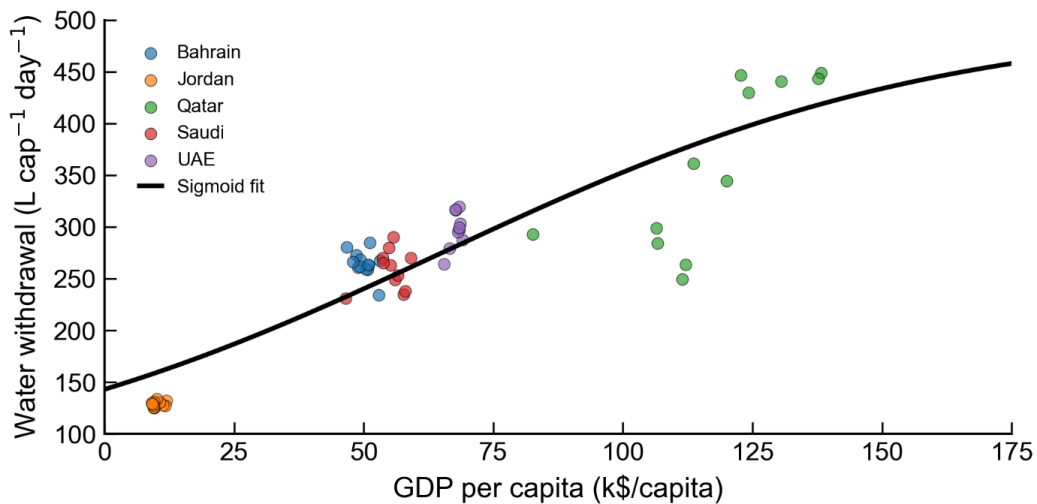
1 The model was developed with an approach in which to estimate $DWW_{pc,t}$ for a given country c and year t by scaling
2 a reference-year value DWW_{pc,t_0} using household size, and economic level:

$$3 \quad DWW_{pc,t} = DWW_{pc,t_0} \times \left(\frac{HHS_{c,t_0}}{HHS_{c,t}} \right)^{0.5} \times \left(\frac{GDPpc_{c,t}}{GDPpc_{c,t_0}} \right)^{0.5} \quad (5)$$

4

5 GDP per capita was adjusted for inflation and expressed in purchasing power parity (PPP) terms at constant 2020
6 prices to enable consistent and comparable cross country analysis (OECD, 2018). The reference year t_0 corresponds
7 to the year with observed domestic water withdrawal data, where t_0 is 2020, while t refers to the year for which the
8 estimate is calculated. This allows reconstruction of domestic water withdrawal time series for any country with a
9 known reference value, explicitly accounting for socio-economic growth, and demographic changes.

10 Following previous studies, domestic water withdrawal (DWW) generally increases with GDP per capita (GDPpc)
11 and exhibits an S-shaped (sigmoid) relationship (Flörke et al., 2013; X. Guo et al., 2022; Zhu et al., 2024). For
12 countries without reported DWW per capita data, a regional sigmoid function was fitted to capture this non-linear
13 trend, as shown in Figure 2. The function is bounded between 50 and 500 liters per capita per day, where 50 L/cap/day
14 corresponds to the basic water requirement recommended by the UN (2024), and 500 L/cap/day represents the highest
15 observed per-capita water use in the region. To ensure temporal consistency, only post-2010 observations were used,
16 as earlier data are influenced by infrastructure expansion and demographic changes that can obscure the GDP–DWW
17 relationship.



18

19 **Figure 2: Sigmoid function fitted to the relationship between per-capita domestic water withdrawal (DWW_{pc}) and GDP**
20 **per capita (2020 PPP), illustrating the non-linear saturation pattern of water use with increasing economic development.**



1 At the regional scale, domestic water withdrawal was integrated with $HCN\%_{r,t}$. Higher household connectivity to
2 the water network leads to increased regional domestic water withdrawal per capita $DWW_{pc,r,t}$. The regional model
3 is expressed as:

$$4 \quad DWW_{pc,r,t} = DWW_{pc,c,t} \times \left(\frac{HHS_{c,t}}{HHS_{r,t}} \right) \times \left(\frac{HCN\%_{r,t}}{HCN\%_{c,t}} \right) \quad (6)$$

5
6 where r denotes the specific region, DWW_{r,t_0} is the reference-year domestic water withdrawal, $HHS_{r,t}$ is the average
7 household size in the region, and $HCN\%_{c,t}$ represents the effect of the percentage of households connected to the
8 water network. Household size and household connectivity are normalized against their corresponding national values
9 for that year. This ensures that the regional estimates reflect concurrent conditions rather than deviations from a fixed
10 baseline year.

11 Domestic water consumption in each spatial cell was derived from the estimated domestic water withdrawal while
12 explicitly accounting for distribution losses and end-use consumption behavior. Let WW denote the total domestic
13 water withdrawal within a grid cell, computed as

$$14 \quad WW_{cell} = DWW_{pc} \cdot Pop_{cell} \quad (7)$$

15
16 where DWW_{pc} is the per-capita domestic water withdrawal and Pop_{cell} is the population of the grid cell.

17 To distinguish between physical losses and effective water use, two parameters were introduced: the non-revenue
18 water fraction (NRW), representing losses within the distribution network, and the consumption factor (CF),
19 representing the proportion of delivered water that is consumptively used by end users. Following proxies from Hejazi
20 et al. (2013) and World Bank (2026b), CF was defined as 0.10 for urban cells and 0.50 for rural cells. NRW estimates,
21 in contrast, rely on region-specific data and, where necessary, fixed values derived from national averages. For Jordan
22 and Oman, NRW ranges between 40–50%; for Bahrain, 23–36%; for Saudi Arabia, 25–40%. In Qatar, reported data
23 indicate a decline from over 35% in the 1990s to 15% in recent years, encompassing both apparent and real losses.
24 For the United Arab Emirates, country-scale NRW values were unavailable; therefore, values were estimated
25 assuming a trajectory similar to Qatar's improvements. A complete summary of data sources is provided in Table 3.

26 Domestic water consumption (WC) per cell is then calculated as

$$27 \quad WC_{cell} = WW_{cell} \cdot NRW_{cell} + WW_{cell} \cdot (1 - NRW_{cell}) \cdot CF_{cell} \quad (8)$$

28
29 The first term represents water losses occurring within the supply network, while the second term quantifies the
30 fraction of effectively delivered water that was consumed. This formulation explicitly separates distribution
31 inefficiencies from end-use consumption, enabling consistent estimation of domestic water consumption across
32 regions with varying infrastructure performance.

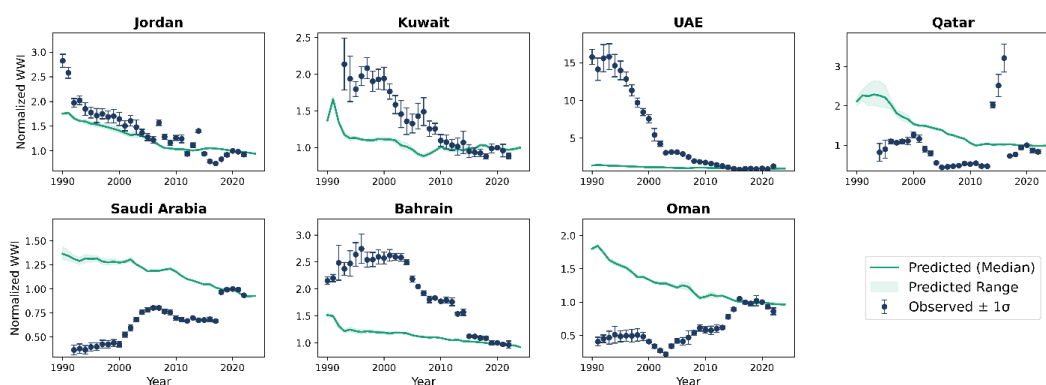


3 Results

3.1 Industrial Water Use

3.1.1 Temporal evolution of techno-economic factors and industrial water use intensity

To evaluate the model accuracy, the techno-economic factor (TEF) was analyzed alongside total industrial water withdrawal intensity, defined as m^3 per unit of energy use. To enable comparison of temporal dynamics across countries, both variables were normalized to their 2020 values, allowing relative changes over time to be assessed, as shown in Figure 3. The analysis is first presented for the GCC countries and Jordan, then extended to a broader set of industrialized countries with long-term data availability (see Supplementary Section S3), supporting further validation of the approach and enabling subsector-level interpretation.



10

11 **Figure 3: Normalized industrial water withdrawal intensity (m^3 per unit of energy use) across countries, where both the**
12 **observed intensity and the techno-economic factor (TEF) are normalized to their respective 2020 values to emphasize**
13 **temporal trends.**

14 Overall, the comparison between modeled and reported industrial water use intensities highlights the model's ability
15 to capture long-term efficiency improvements, structural changes, and cross-country heterogeneity. Deviations were
16 most pronounced in earlier decades and in countries with limited, aggregated, or inconsistent historical data, as shown
17 in Figure 3. Clear inconsistencies in reporting and possible mis-documentation are apparent in some countries, most
18 notably Saudi Arabia, UAE, Qatar, and Oman during the early decades. Those results demonstrate that high-resolution,
19 process-informed modeling can reveal systematic temporal patterns in industrial water use even where observational
20 records are incomplete, providing a model for evaluating historical trends and supporting future resource management.
21 The GCC countries exhibit broadly similar trajectories, characterized by initially high or relatively stable industrial
22 water-use intensities followed by gradual and sustained declines over time. The modeled results indicate progressive
23 improvements in industrial water-use efficiency associated with technological modernization, process optimization,
24 and evolving production practices. Several country-specific features are evident in the comparison with reported data.
25 In the UAE, discrepancies may partly reflect the inclusion of cooling-water withdrawals within total industrial water-
26 use statistics, which can substantially influence reported intensities. Qatar exhibits unusually high reported values



1 during the period surrounding the rapid infrastructure expansion associated with preparations for the 2022 FIFA World
2 Cup, resulting in pronounced deviations from the modeled trend. Kuwait shows considerable uncertainty in the
3 observed record, making long-term trends more difficult to interpret. Bahrain displays a sudden decline in reported
4 intensity that is not fully reflected in the modeled series, suggesting a possible change in reporting practices or data
5 classification. In Oman and Saudi Arabia, observed values appear to exclude some industrial water use sectors in
6 certain years, contributing to differences between reported and modeled estimates.
7 Jordan differs somewhat from the Gulf countries by exhibiting a smoother and more gradual decline in industrial water
8 use intensity throughout the study period. Both modeled and observed series indicate continuous efficiency
9 improvements with relatively limited variability, suggesting that long-term changes were driven primarily by
10 incremental technological advances rather than major shifts in industrial composition. Although the available data
11 does not allow definitive identification of structural transitions, the close correspondence between modeled and
12 reported values underscores the importance of consistent sectoral reporting for capturing long-term efficiency trends.
13

14 **3.1.2 Validation of Sub-Sector Efficiency Changes**

15 To assess the applicability of the overall TEF-based formulation at finer industrial scales, we conducted a validation
16 exercise at the sub-sector level. Given the limited availability of historical water withdrawal intensity data
17 disaggregated by sub-sector, the analysis included only four industrial sub-sectors: petro-refining, paper and pulp
18 production, food and beverage manufacturing, and basic metals production, where relatively consistent data records
19 are available. The validation was supplemented using datasets from other countries, enabling both a more robust
20 evaluation of model performance and an assessment of its broader, global applicability across diverse industrial
21 contexts. Both observed and modeled water withdrawal intensities were normalized to a common reference year to
22 facilitate direct comparison of temporal dynamics and to highlight the magnitude of efficiency evolution captured by
23 the model, as shown in Figure 4.

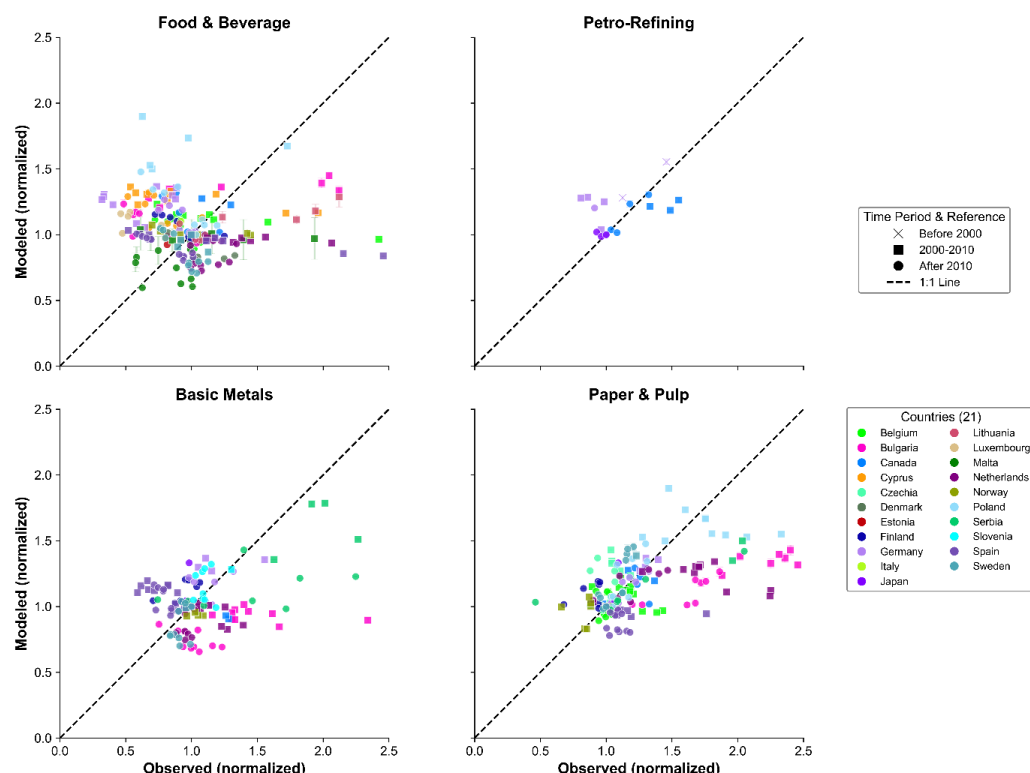


Figure 4: Comparison of modeled versus observed industrial water-use intensity at the sub-sector level for four representative industries: (a) food and beverage manufacturing, (b) petro refining, (c) basic metals production, (d) paper and pulp manufacturing. For each sub-sector, values are normalized to a common reference year to allow comparison of temporal changes in efficiency. The solid line represents the 1:1 relationship between modeled and observed intensities.

For petro-refining, the modeled intensities generally align with reported values across most countries, indicating a robust representation of efficiency dynamics. Basic metals production shows a similarly strong correspondence, with most countries closely clustered around the 1:1 line. Deviations are observed in countries such as Serbia and Bulgaria, which may reflect limitations in the reported data, potential structural differences not fully captured by the model, or residual uncertainties in sub-sector-specific efficiency dynamics.

For paper and pulp production, the model reproduced the overall trend well; however, similar deviations are observed for Serbia and Bulgaria, while other countries remain closely aligned with the 1:1 expectation. In the food and beverage sector, certain countries, such as Malta, exhibited substantial uncertainty, and outliers are also apparent for Belgium, reflecting both reporting inconsistencies and sub-sector-specific variability that may not be fully resolved in the modeled TEF.

Overall, these comparisons demonstrated that the TEF-based formulation captures the dominant efficiency dynamics across sub-sectors, while transparently revealing regions and periods where data limitations or structural heterogeneity



1 introduce discrepancies. This sub-sectoral validation provides confidence in applying the model to estimate temporal
2 changes in water-use efficiency, even in contexts with sparse observational data.

3 **3.1.3 Industrial Water Use in the GCC countries and Jordan**

4 Across the GCC and Jordan, industrial freshwater withdrawal and consumption trajectories indicate a progressive
5 restructuring of sub-sectoral water use, closely aligned with national industrialization and economic diversification
6 pathways, as shown in Figure 5. Within the present model, these trajectories emerge not only as a reflection of
7 efficiency changes but as a direct outcome of a bottom-up formulation in which total industrial water use is computed
8 as the product of sectoral production output and time-evolving water use intensities, as shown in Figure 4. This allows
9 structural changes in production composition and efficiency-driven intensity reductions to be explicitly captured
10 within the modeled pathways. Consequently, differences in both the evolution of production structures and country-
11 specific TEF dynamics jointly govern the curvature, divergence, and relative stability of the simulated water use
12 trajectories.

13 Bahrain and the UAE illustrate this transformation most clearly. In both countries, early water use patterns were
14 historically dominated by petro-refining, which gradually transitioned toward a more diversified configuration led by
15 secondary metallurgy (particularly primary aluminum and steel) alongside a growing contribution from the food &
16 beverage sector. This evolution reflects a broader shift toward downstream manufacturing, defined here as value-
17 added industrial activities that process primary commodities and raw materials into higher-value intermediate or
18 finished products, including metal fabrication, processed materials, and consumer-oriented goods, thereby increasing
19 domestic value retention and industrial complexity. In this context, downstream industrial expansion has altered water
20 use structures by introducing a wider mix of process-intensive sectors beyond basic hydrocarbon refining. These
21 changes were consistent with long-term national diversification strategies aimed at reducing dependence on upstream
22 extractive industries and strengthening manufacturing capacity, as articulated in policy frameworks such as Bahrain
23 Economic Vision 2030, UAE Industrial Strategy 2031 (Bahrain, 2008; UAE, 2024).

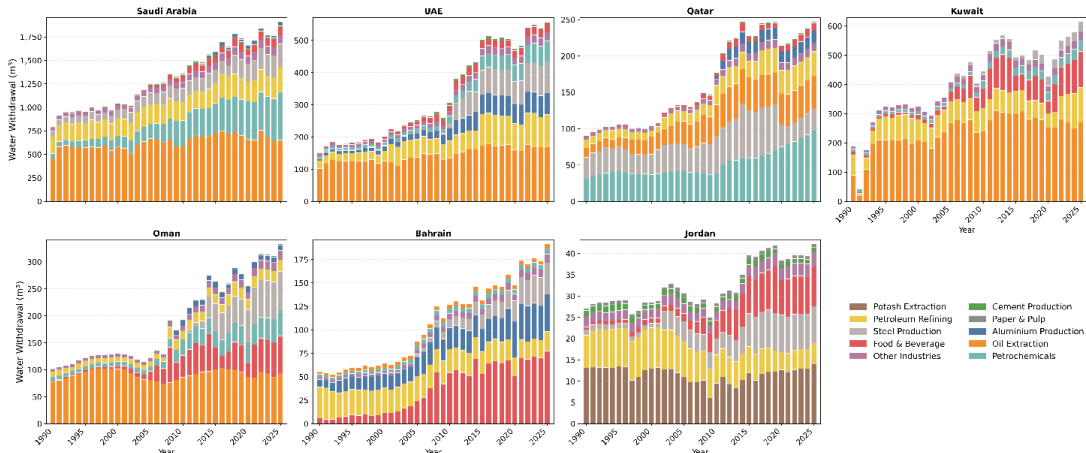
24 In Saudi Arabia, industrial water use remains heavily influenced by the oil, and chemical and petrochemical sectors,
25 which continues to anchor national use despite the expansion of other subsectors. The persistence of this dominance
26 highlights the scale and resource intensity of integrated industrial clusters, where petrochemical complexes function
27 as long-term stabilizers of water use. The gradual emergence of steel, aluminum, and food processing introduces
28 additional components into the sectoral aggregation; however, because their relative production shares remain
29 secondary, they contribute more to incremental uplift than to structural reconfiguration of the overall water use
30 pathway.

31 Qatar exhibits an intermediate trajectory, characterized by the expansion of aluminum and steel industries
32 superimposed upon an established petrochemical and refining base. Kuwait and Oman maintain stronger continuity
33 with hydrocarbon-centered use structures, where oil extraction continues to play a dominant role in industrial water
34 withdrawal. Nonetheless, both countries display gradual broadening of sectoral contributions through the increasing
35 presence of steel and food processing activities, suggesting incremental diversification within resource-dependent
36 economies. Jordan's trajectory diverges fundamentally from the GCC pattern. Early industrial water use was primarily



1 shaped by potash mining, followed by a more diversified structure associated with the growth of steel and food-related
2 industries. This pathway reflects resource-constrained industrial development distinct from hydrocarbon-rich
3 neighbors.
4 At the country scale, the observed patterns point not merely to growth, but to a qualitative reconfiguration of industrial
5 water use. The drivers of freshwater use increasingly reflect manufacturing-oriented expansion rather than exclusive
6 reliance on upstream extractive activities. Energy-intensive industries, particularly secondary metallurgy and
7 downstream processing industries, emerge as progressively influential components of the regional water use structure.
8 Concurrently, traditional hydrocarbon subsectors exhibit relative stabilization in their proportional contributions. This
9 evolving balance indicates a transition in how industrialization manifests in water use dynamics, from extraction-
10 dominated regimes toward diversified production systems. The redistribution of use across subsectors signals
11 intensifying intersectoral competition for freshwater resources and highlights the growing importance of efficiency
12 improvements, technological adaptation, and integrated water resource planning. Ultimately, regional industrial water
13 trajectories mirror broader economic transitions, where diversification policies and industrial modernization were
14 directly encoded in shifting water allocation patterns.
15 Industrial development across the GCC is strongly concentrated in coastal zones, where water and energy-intensive
16 sectors such as petrochemical plants, refineries, steelworks, and aluminum smelters are mainly located to use seawater
17 for cooling and industrial processes, reducing dependence on inland freshwater resources, as shown in Figure 7. This
18 spatial clustering is important because industrial water use is therefore not evenly distributed, but concentrated in a
19 limited number of major coastal hubs. As a result, national-level estimates of industrial water use are largely driven
20 by the activity of these hubs, which can influence the interpretation of temporal changes in water demand. In this
21 context, variations in total industrial water use may reflect shifts in the geographic distribution of industrial growth—
22 particularly expansion in coastal, water-intensive clusters—rather than only changes in overall economic activity.

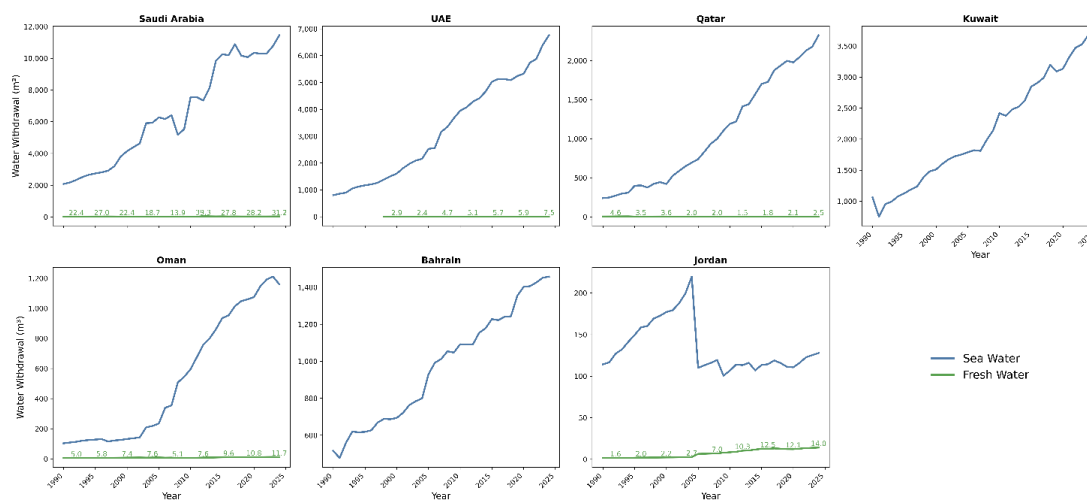
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24

25 **Figure 5: Temporal trends in industrial water withdrawal across various subsectors from 1990 to 2025.**

26



1

2 **Figure 6: Electricity generation water withdrawal trends from 1990-2025.**

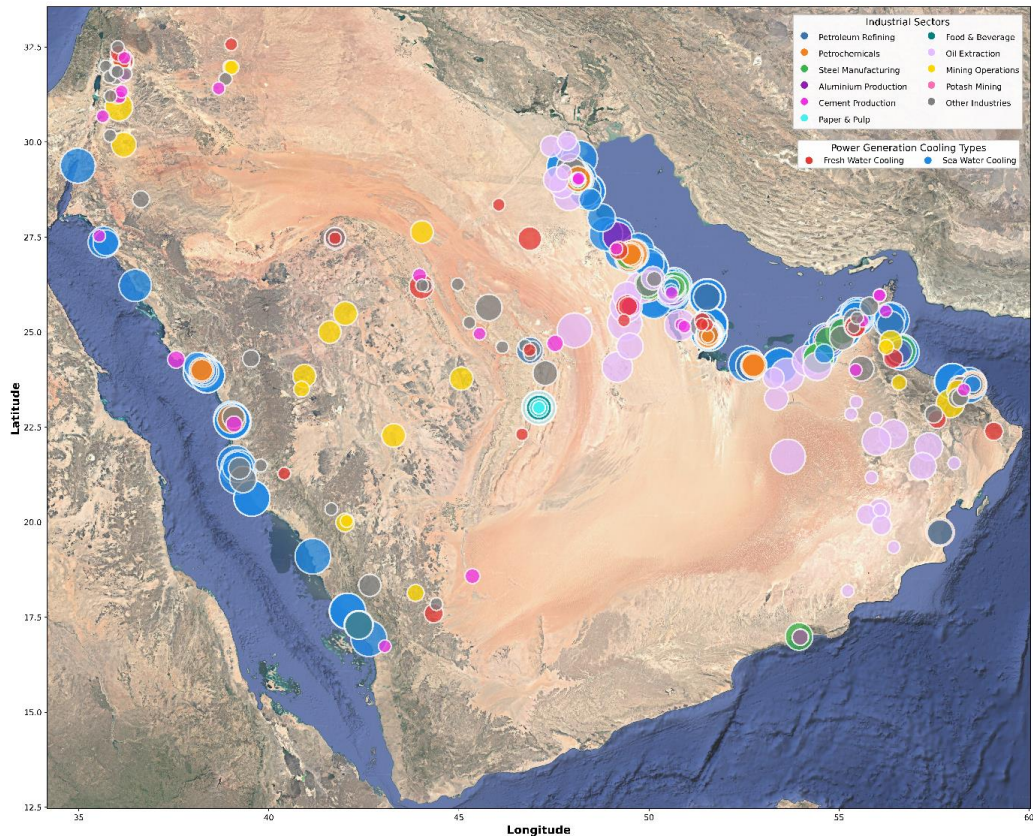


Figure 7: Geographic representation of annual water withdrawal per plant (2025). To facilitate visualization of both fine-scale location patterns and coarse relative magnitudes, circle areas are scaled to withdrawal volumes with lower and upper bounds; this prevents oversizing at high-volume sites while preserving density-based spatial information, Map data © Google, accessed via Google Maps on [Jan-2026].

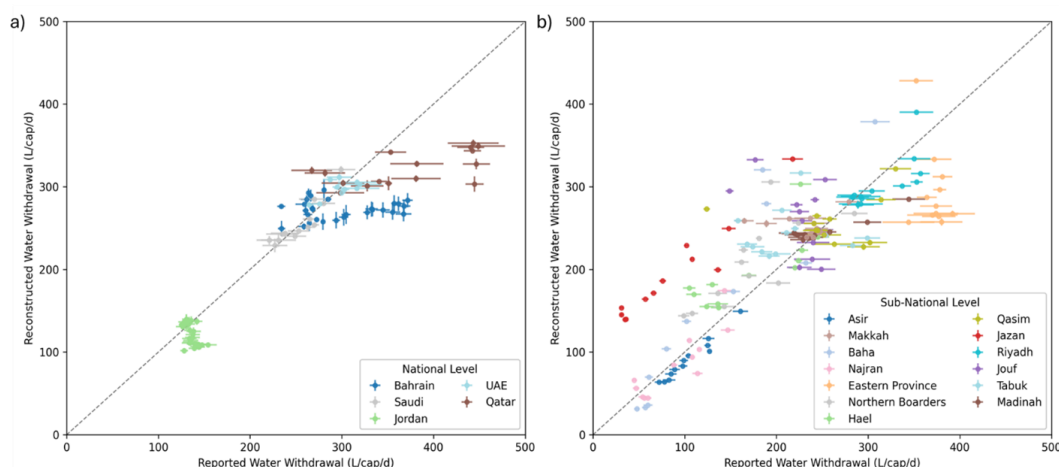
3.2 Domestic Water Use

3.2.1 Reconstructed data accuracy

The reconstructed water use estimates were evaluated against available governmental reports and widely used global datasets to examine their consistency and robustness. Uncertainty associated with the observed values partly reflects discrepancies in population estimates across different sources, which directly propagate into reported water use values. For the reconstructed estimates, the spread shown in Figure 8 at both the country and regional scales reflect differences among the input datasets, including variations in assumptions, temporal coverage, and reporting conventions. At the sub-national scale, the reconstructed estimates show a tendency toward higher values relative to reported figures. This behavior can be linked to limitations in the available observational data, including the use of legacy datasets in some regions that may not fully capture recent changes in water use patterns, the presence of very low



1 reported values in certain cases, and the incomplete representation of unregulated or informal water withdrawals in
2 official country reports. Consequently, part of the apparent discrepancy likely reflects structural uncertainties and
3 inconsistencies in the underlying datasets rather than systematic bias in the reconstruction approach itself.



4
5 **Figure 8: Evaluation of reconstruction accuracy at multiple spatial scales. (a) National level validation of reconstructed**
6 **water-use estimates against reported values. (b) Sub-National level assessment of reconstruction accuracy across regions.**

7 3.2.2 Domestic Withdrawal & Consumption

8 As shown in Figure 9 and Figure 10, per capita water withdrawal and consumption across the Middle East exhibit
9 both growth and redistribution patterns. Saudi Arabia, the UAE, and Qatar consistently recorded the highest
10 withdrawals, while Bahrain, Jordan, Kuwait, and Oman experienced more moderate increases, largely reflecting
11 national GDP per capita growth and reductions in household size. At finer temporal resolution, the model captures
12 country-specific variations, such as the impact of the Kuwait War in 1991 and infrastructure preparations in Qatar
13 ahead of the 2022 FIFA World Cup. Figure 8 also reveal deviations during these periods, likely reflecting reporting
14 inconsistencies or documentation gaps in domestic water use data.

15 Domestic water consumption generally increased more gradually. Consumption to withdrawal ratios declined in
16 several countries, particularly in the UAE and Qatar, suggesting improvements in network efficiency, reductions in
17 system losses, and the influence of urbanization. In Bahrain and Saudi Arabia, consumption trends show moderate
18 increases, with fluctuations that closely follow national development trajectories.

19 At the sub-national scale, Saudi regions exhibited marked heterogeneity in both withdrawal and consumption. Regions
20 such as Baha and Asir experienced the largest relative growth, mainly governed by infrastructure development.
21 Consumption followed similar patterns but with slightly lower rates, leading to an increasing consumption-to-
22 withdrawal ratio in these rapidly developing regions, particularly after 2010. In contrast, established urbanized regions
23 such as Riyadh, Makkah, and Madinah maintained relatively stable withdrawals and consumption, reflecting mature
24 water infrastructure, efficient distribution networks, and consistent household water use. Northern and central regions,



1 including Qasim, Tabuk, and Northern Borders, displayed steady growth in both withdrawal and consumption,
2 reflecting a combination of socioeconomic and infrastructure improvements.
3 These results demonstrate that water withdrawal and consumption patterns are governed by complementary but
4 distinct drivers across scales. At the national level, fluctuations in withdrawals closely follow economic growth and
5 changes in household size, whereas consumption trends are increasingly shaped by network efficiency improvements
6 and urbanization level. At the sub-national scale, regional variability reflects the interplay of local industrialization,
7 infrastructure development, and demographic dynamics, with rapidly developing regions exhibiting the largest
8 proportional increases in both withdrawal and consumption. Collectively, these findings emphasize that both
9 macroeconomic planning and targeted regional interventions are essential to manage water use sustainably and to
10 optimize the consumption-to-withdrawal balance.

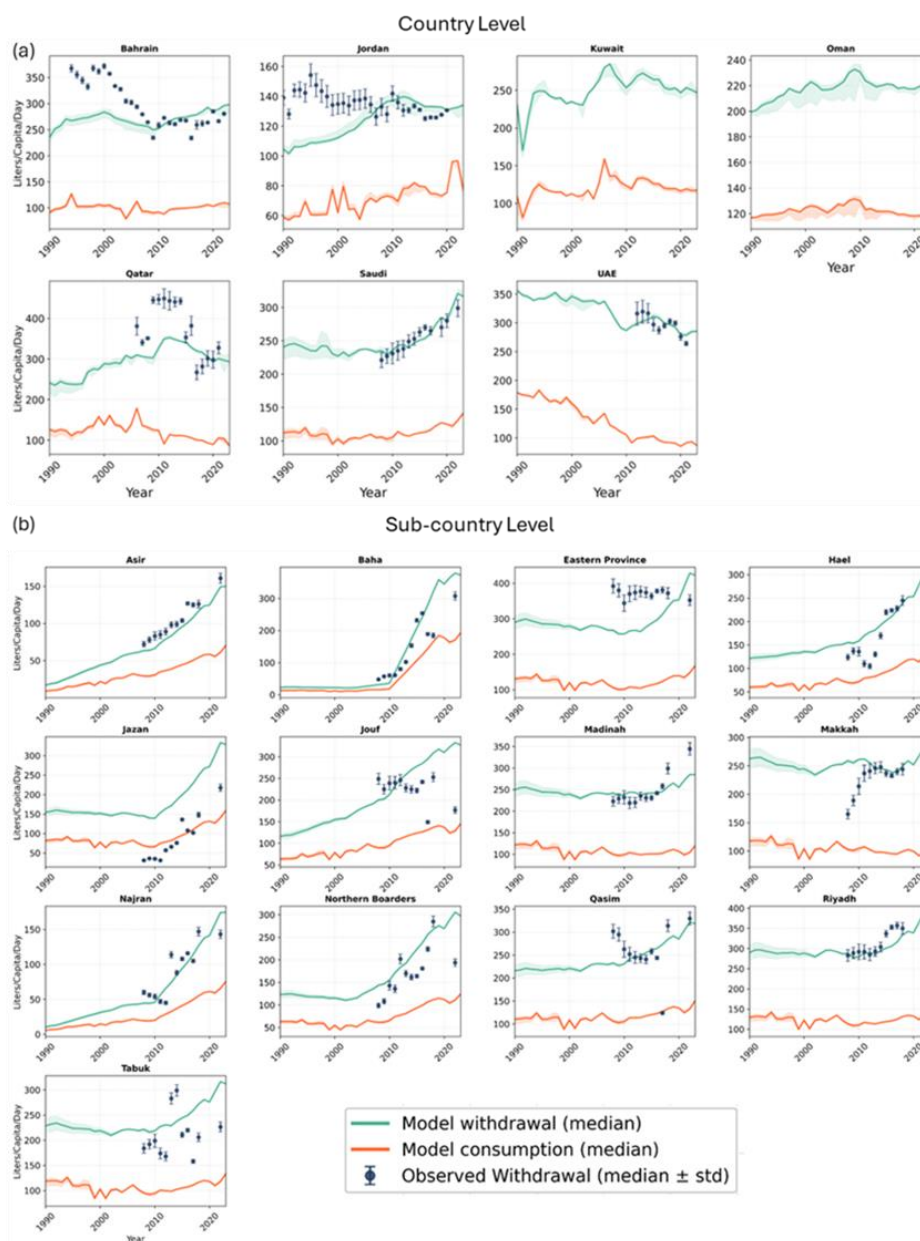


Figure 9: Observed industrial water withdrawal alongside reconstructed withdrawal and consumption. Panel (a) presents data for individual countries, while panel (b) focuses on regions within Saudi Arabia. Both observed and reconstructed values are shown with uncertainty ranges, depicted as the median $\pm$ standard deviation, to illustrate variability in the reconstruction.

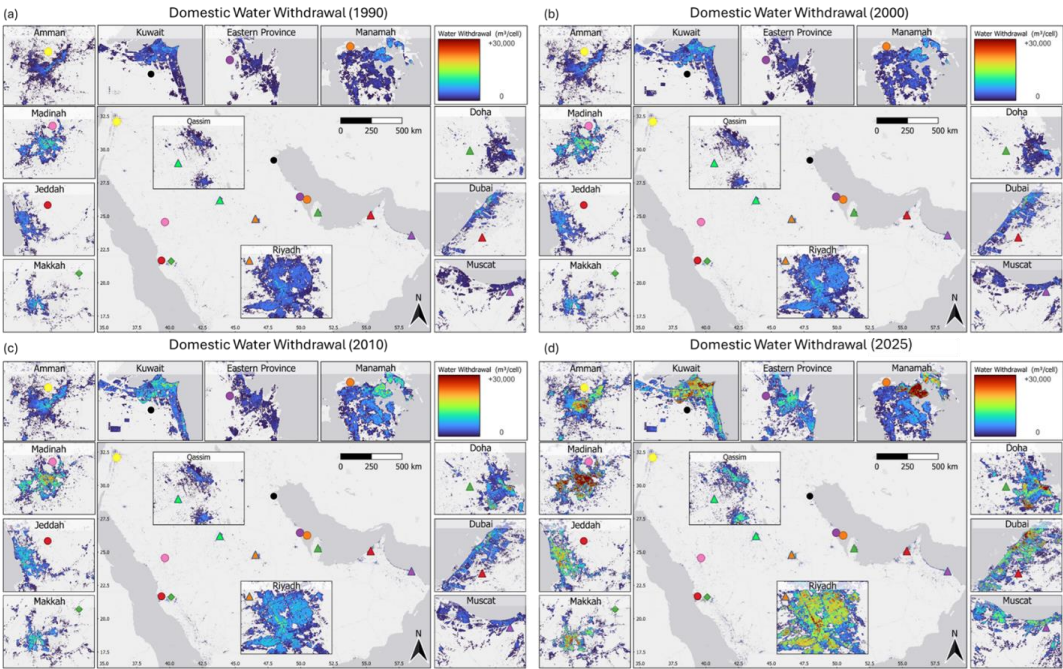


Figure 10: Gridded domestic water withdrawal data at 3 arcseconds resolution (~90m), showing spatial differences across four panels: (a) 1990, (b) 2000, (c) 2010, and (d) 2025. Markers indicate selected locations on the main map that are replicated on the sub-national inset maps to facilitate direct comparison and interpretation. Note that sub-national inset plots use varying scales and differ from the main panel to better highlight regional patterns.

4 Discussion

This study develops a regional water use model that integrates a disaggregated industrial structure with a domestic model, improving consistency between water withdrawal, consumption, and losses across heterogeneous socio-economic contexts. A key advancement is the explicit representation of industrial water use through the subsector disaggregation, which distinguishes major industrial pathways, allowing variation in water intensity to emerge from differences in production structure, technological development, and subsector composition. Compared to highly aggregated global approaches, this structure better captures heterogeneity in industrial water use that is otherwise obscured. In parallel, the domestic model refines the representation of household water use by separating urban and rural water use, thereby accounting for differences in infrastructure access, lifestyle patterns, and demographic composition that shape consumption behavior. Together, these components establish a more coherent linkage between water withdrawals, consumption, and losses across industrial and domestic sectors, while remaining scalable across regions and enabling more meaningful inter-regional comparisons by resolving key spatial heterogeneities in water use drivers. However, despite these improvements, the model remains a simplified representation of real-world



1 systems, and its outputs should be interpreted in light of structural and data-driven uncertainties rather than as fully
2 resolved physical reconstructions.

3 Although at the industrial level the model introduces a sub-sectoral structure that improves upon a lump-sum single-
4 sector representation, yet important limitations remain in how individual subsectors are resolved. In electricity
5 generation, water use was differentiated by plant type and cooling technology. However, the lack of consistent, time-
6 varying data on technological change and efficiency evolution hinders the ability to fully capture long-term transitions
7 in water intensity, creating uncertainty around the temporal dynamics of cooling water use.

8 In the petrochemical and petroleum refining sectors, water use was represented in an aggregated form across complex
9 and highly diverse production chains. As a result, variations in specific refinery configurations, product slates, and
10 process pathways are not explicitly resolved, introducing uncertainty related to intra-sector variability and process-
11 level water allocation. In the basic metals sector, the absence of detailed differentiation between production routes
12 such as furnace types or ore-processing pathways limits the representation of structural shifts in industrial water use,
13 leading to uncertainty about efficiency-driven changes in metals production.

14 An additional limitation arises in the food and beverage sector, where water use is rarely documented using consistent
15 physical output metrics across countries. Instead, estimates rely on indirect economic or aggregated proxies, which
16 introduce uncertainty in translating economic activity into physical water intensity. Overall, these industrial limitations
17 stem primarily from constrained availability of harmonized, time-resolved sub-sectoral datasets, which restrict the
18 extent to which technological heterogeneity and structural change can be explicitly represented. As a result, the model
19 is expected to perform more robustly in capturing broad inter-sectoral and inter-country contrasts than fine-scale
20 temporal dynamics within individual industrial subsectors.

21 For domestic water use, uncertainty arises primarily from demographic reconstruction and infrastructure
22 representation. In several cases, population data prior to consistent census reporting periods (e.g., Saudi Arabia before
23 2010) were estimated using harmonized ratios across datasets, introducing uncertainty in per-capita water allocation
24 and potentially affecting inter-temporal comparability. In the UAE, the absence of direct household size data
25 necessitated the use of proxy values from neighboring regional contexts, introducing structural assumptions that affect
26 estimated domestic use levels. Additionally, non-revenue water (NRW), which is inconsistently reported across
27 countries, is a key unobserved component that affects the relationship between consumption and abstraction. Together,
28 these factors highlight that domestic water use estimates are sensitive not only to demographic assumptions but also
29 to incomplete characterization of distribution network efficiency, reinforcing that model outputs should be interpreted
30 as constrained estimates rather than fully observed quantities.

31 Nevertheless, validation results indicate that the framework successfully reproduces the dominant temporal and spatial
32 patterns of water use across the study region. The model therefore provides a useful platform for investigating
33 historical water-use dynamics, evaluating future development pathways, and supporting integrated assessments of
34 water, energy, and industrial systems. More broadly, the results suggest that explicit representation of industrial
35 structure, infrastructure efficiency, and spatial heterogeneity can substantially improve regional water-use modeling
36 compared with conventional aggregated approaches.

37



1 **Code and data availability**

2 All code and data used in HyDRA version 1.0 for model development and generation of the results presented in this
3 study are publicly available at <https://doi.org/10.5281/zenodo.20788533> (Al-Zu'bi & Wada, 2026)

4 **Supplement link**

5 The supplementary material is provided as a separate file, and published with this article.

6 **Author contributions**

7 AAZ collected the data, performed the data analysis, model formulation, implementation, and the development of the
8 HyDRA (version 1.0) framework, and wrote the original manuscript. YW conceived the study, performed the model
9 formulation and development of the HyDRA (version 1.0), wrote and reviewed the manuscript, and provided overall
10 supervision of the study, secured funding support.

11 **Competing interests**

12 The contact author has declared that none of the authors has any competing interests.

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18 **References**

19 Abushammala, M. F. M. (2017). *Domestic water demand forecasting for Makkah, Saudi Arabia*.
20 Ahmed, V., Saad, A., Saleh, H., Saboor, S., Kasianov, N., & Alnaqbi, T. (2020). *Implementation of water demand*
21 *forecasting model to aid sustainable water supply chain management in UAE*.
22 https://www.preprints.org/frontend/manuscript/120f6d90b74e712f5fd33b7d7c81a04d/download_pub



- 1 Al Dhaif, R., Ibrahim, A. F., Elkatatny, S., & Al Shehri, D. (2021). Prediction of oil rates using Machine Learning for
2 high gas oil ratio and water cut reservoirs. *Flow Measurement and Instrumentation*, 82(102065).
3 <https://doi.org/10.1016/j.flowmeasinst.2021.102065>
- 4 Alazmi, H. J., Mitchell, G., & Trigg, M. A. (2024). Kuwait household water demand in 2050: Spatial microsimulation
5 and impact appraisal. *Water and Environment Journal*, 38(1), 139–152. <https://doi.org/10.1111/wej.12906>
- 6 Al-Bulushi, M., Al Sulti, M., & Abushammala, M. (2018). Investigation of Water Losses in Water Supply System:
7 Muscat as a Case Study. *MATEC Web of Conferences*, 203, 07004.
8 <https://doi.org/10.1051/mateconf/201820307004>
- 9 Alcamo, J., Döll, P., Henrichs, T., Kaspar, F., Lehner, B., Rösch, T., & Siebert, S. (2003). Development and testing
10 of the WaterGAP 2 global model of water use and availability. *Hydrological Sciences Journal*, 48(3), 317–
11 337. <https://doi.org/10.1623/hysj.48.3.317.45290>
- 12 Alcamo, J., Flörke, M., & Märker, M. (2007). Future long-term changes in global water resources driven by socio-
13 economic and climatic changes. *Hydrological Sciences Journal*, 52(2), 247–275.
14 <https://doi.org/10.1623/hysj.52.2.247>
- 15 Alfalah, O. (2021). Estimating residential demand for water in Kuwait: A cointegration analysis. *International Journal*
16 *of Energy Economics and Policy*, 11(4), 283–287.
- 17 Ali, B., & Kumar, A. (2017). Life cycle water demand coefficients for crude oil production from five North American
18 locations. *Water Research*, 123, 290–300.
- 19 Ali, Mortula, M. M., & Gawai, R. (2024). A GIS-Based Tool for Leak Detection in Water Distribution Networks
20 (WDNs). *Recent Advances in Environmental Science from the Euro-Mediterranean and Surrounding*
21 *Regions (4th Edition) - Proceedings of 4th Euro-Mediterranean Conference for Environmental Integration*
22 *EMCEI-4, 2022*, 737–740. https://doi.org/10.1007/978-3-031-51904-8_161
- 23 Al-Khalid, A., Al-Senafy, M., & Azrag, E. (2013). *Estimation Of Leakage From The Freshwater Network In Kuwait*.
24 <https://www.witpress.com/elibrary/wit-transactions-on-ecology-and-the-environment/171/24611>
- 25 Alkhanbashi, A., & Al Shuaili, A. (2026). *Economic Efficiency and Regulation in Oman's Water Sector: A*
26 *Microeconomic Analysis of Nama Water Services*
 (SSRN Scholarly Paper 6757766). Social Science
27 Research Network. <https://doi.org/10.2139/ssrn.6757766>



- 1 Al-Maadid, A., Akesson, J., Bernstein, D. H., Chakravarti, J., & Khalifa, A. (2023). Understanding Water
2 Consumption in Qatar: Evidence From a Nationally Representative Survey. *Urban Water Journal*, 20(10),
3 1450–1461. <https://doi.org/10.1080/1573062X.2022.2036201>
- 4 Almulhim, A. I., & Abubakar, I. R. (2024). A segmentation approach to understanding water consumption behavioral
5 patterns among households in Saudi Arabia for a sustainable future. *Resources, Environment and*
6 *Sustainability*, 15, 100144.
- 7 Almutaz, I., Ajbar, A. H., & Ali, E. (2012). Determinants of residential water demand in an arid and oil rich country:
8 A case study of Riyadh city in Saudi Arabia. *Int. J. Phys. Sci.*
- 9 Al-Najjar, F. O., Al-Karablieh, E. K., & Salman, A. (2011). Residential Water Demand Elasticity in Greater Amman
10 Area. *Jordan Journal of Agricultural Sciences*, 7(1).
11 [https://www.academia.edu/download/72117004/Residential_Water_Demand_Elasticity_in_G20211010-](https://www.academia.edu/download/72117004/Residential_Water_Demand_Elasticity_in_G20211010-26561-1s92ka1.pdf)
12 [26561-1s92ka1.pdf](https://www.academia.edu/download/72117004/Residential_Water_Demand_Elasticity_in_G20211010-26561-1s92ka1.pdf)
- 13 Alqahtani, S. H., Alropy, E. T., Kotb, A. A., & Alaagib, S. E. B. (2021). Estimation of the standard model of the water
14 footprint of individuals in the Kingdom of Saudi Arabia. *Arabian Journal of Geosciences*, 14(8), 695.
15 <https://doi.org/10.1007/s12517-021-07047-w>
- 16 Al-Zubari, W., Al-Turbak, A., Zahid, W., Al-Ruwis, K., Al-Tkhais, A., Al-Muataz, I., Abdelwahab, A., Murad, A.,
17 Al-Harbi, M., & Al-Sulaymani, Z. (2017). An overview of the GCC Unified Water Strategy (2016–2035).
18 *Desalination and Water Treatment*, 81, 1–18. <https://doi.org/10.5004/dwt.2017.20864>
- 19 Al-Zu'bi, A., Elborolusy, Y., Hejazi, M., & Wada, Y. (2025). Water-Resilient Cities: GCC Strategies and Policy
20 Recommendations. In A. Arora, F. Belaïd, & S. Lechtenberg-Kasten (Eds.), *Climate-Resilient Cities* (pp. 89–
21 102). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-73090-0_5
- 22 Al-Zu'bi, A., & Wada, Y. (2026). *amrhz1/HyDRA_v_1: HyDRA_v_1*. <https://doi.org/10.5281/zenodo.20788533>
- 23 Andersen, P., Djurhuus, K., Askarinezhad, R., & Solbakken, J. S. (2022). *Management of High-Water-Cut and Mature*
24 *Petroleum Reservoirs. Energies* 2022, 15, 8344. s Note: MDPI stays neu-tral with regard to jurisdictional
25 claims in [https://www.researchgate.net/profile/Pal-](https://www.researchgate.net/profile/Pal-Andersen/publication/365183258_Management_of_High-Water-Cut_and_Mature_Petroleum_Reservoirs/links/636a7f2954eb5f547cb3367a/Management-of-High-Water-Cut-and-Mature-Petroleum-Reservoirs.pdf)
26 [Andersen/publication/365183258_Management_of_High-Water-](https://www.researchgate.net/profile/Pal-Andersen/publication/365183258_Management_of_High-Water-Cut_and_Mature_Petroleum_Reservoirs/links/636a7f2954eb5f547cb3367a/Management-of-High-Water-Cut-and-Mature-Petroleum-Reservoirs.pdf)
27 [Cut_and_Mature_Petroleum_Reservoirs/links/636a7f2954eb5f547cb3367a/Management-of-High-Water-](https://www.researchgate.net/profile/Pal-Andersen/publication/365183258_Management_of_High-Water-Cut_and_Mature_Petroleum_Reservoirs/links/636a7f2954eb5f547cb3367a/Management-of-High-Water-Cut-and-Mature-Petroleum-Reservoirs.pdf)
28 [Cut-and-Mature-Petroleum-Reservoirs.pdf](https://www.researchgate.net/profile/Pal-Andersen/publication/365183258_Management_of_High-Water-Cut_and_Mature_Petroleum_Reservoirs/links/636a7f2954eb5f547cb3367a/Management-of-High-Water-Cut-and-Mature-Petroleum-Reservoirs.pdf)



- 1 APC. (1999). *Arab Potash Company Annual Report*.
- 2 APC. (2002). *Arab Potash Company Annual Report*.
- 3 APC. (2007). *Arab Potash Company Annual Report*.
- 4 APC. (2011). *Arab Potash Company Annual Report*.
- 5 APC. (2016). *Arab Potash Company Annual Report*.
- 6 APC. (2021). 2021 Sustainability Report.
7 https://www.arabpotash.com/ebv4.0/root_storage/en/eb_list_page/2022_sustainability_report.pdf
- 8 APC. (2022). 2022 Sustainability Report.
9 https://www.arabpotash.com/ebv4.0/root_storage/en/eb_list_page/2022_sustainability_report.pdf
- 10 APC. (2025). *Arab Potash Company Annual Report*.
- 11 Arafin, S., Al-Habsi, N., & Mujibur Rahman, S. M. (2012). Transport properties and model-based dynamical
12 properties of Omani crude oils. *Arabian Journal of Geosciences*, 5(5), 1085–1092.
13 <https://doi.org/10.1007/s12517-011-0301-z>
- 14 Atimtay, A. T., & Sikdar, S. K. (2011). *Security of industrial water supply and management*. Springer.
15 <https://books.google.com/books?hl=en&lr=&id=myfyCAAQBAJ&oi=fnd&pg=PR3&dq=Atimtay,+A.+T>
16 [,+%26+Sikdar,+S.+K.+\(2011\).+Security+of+industrial+water+supply+and+management.+Springer.&ots=](https://books.google.com/books?hl=en&lr=&id=myfyCAAQBAJ&oi=fnd&pg=PR3&dq=Atimtay,+A.+T)
17 [xu7ULmiGvF&sig=L6n7ASA6ApmP09-MVmBF3ZC9h8](https://books.google.com/books?hl=en&lr=&id=myfyCAAQBAJ&oi=fnd&pg=PR3&dq=Atimtay,+A.+T)
- 18 Babel, M. S., Gupta, A. D., & Pradhan, P. (2007). A multivariate econometric approach for domestic water demand
19 modeling: An application to Kathmandu, Nepal. *Water Resources Management*, 21(3), 573–589.
20 <https://doi.org/10.1007/s11269-006-9030-6>
- 21 Bahrain. (2008). *Bahrain Economic Vision 2030—Prime Minister's Office | Kingdom of Bahrain*.
22 <https://www.pmo.gov.bh/en/category/bahrain-economic-vision-2030>
- 23 Baniasad, A., Littke, R., & Abeed, Q. (2023). PETROLEUM SYSTEMS ANALYSIS OF THE EASTERN
24 ARABIAN PLATE: CHEMOMETRICS BASED ON A REVIEW OF THE GEOCHEMICAL
25 CHARACTERISTICS OF OILS IN JURASSIC – CENOZOIC RESERVOIRS. *Journal of Petroleum*
26 *Geology*, 46(1), 3–45. <https://doi.org/10.1111/jpg.12829>



- 1 Bata, M. H., Carriveau, R., & Ting, D. S.-K. (2020). Short-Term Water Demand Forecasting Using Nonlinear
2 Autoregressive Artificial Neural Networks. *Journal of Water Resources Planning and Management*, 146(3),
3 04020008. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0001165](https://doi.org/10.1061/(ASCE)WR.1943-5452.0001165)
- 4 Bijl, D. L., Biemans, H., Bogaart, P. W., Dekker, S. C., Doelman, J. C., Stehfest, E., & Van Vuuren, D. P. (2018). A
5 Global Analysis of Future Water Deficit Based On Different Allocation Mechanisms. *Water Resources*
6 *Research*, 54(8), 5803–5824. <https://doi.org/10.1029/2017WR021688>
- 7 Blanc, E., Strzepek, K., Schlosser, A., Jacoby, H., Gueneau, A., Fant, C., Rausch, S., & Reilly, J. (2014). Modeling
8 U.S. water resources under climate change. *Earth's Future*, 2(4), 197–224.
9 <https://doi.org/10.1002/2013EF000214>
- 10 Boretti, A., & Rosa, L. (2019). Reassessing the projections of the world water development report. *NPJ Clean Water*,
11 2(1), 15.
- 12 Buzzi Unicem. (2021). *Sustainability Report 2021*.
- 13 Byers, E. A., Hall, J. W., & Amezaga, J. M. (2014). Electricity generation and cooling water use: UK pathways to
14 2050. *Global Environmental Change*, 25, 16–30.
- 15 Byers, Friedrich, J., Hennig, R., Kressig, A., Li, X., Valeri, L. M., & McCormick, C. (2018). *A global database of*
16 *power plants*. <https://www.wri.org/research/global-database-power-plants>
- 17 Canada Statistics. (2019). *Industrial Water Use* [Dataset].
- 18 Cazcarro, I., Duarte, R., & Sánchez-Chóliz, J. (2013). Economic growth and the evolution of water consumption in
19 Spain: A structural decomposition analysis. *Ecological Economics*, 96, 51–61.
- 20 Chengkang, G., Dan, W., Hui, D., Jiuju, C., Weiguang, Z., & Tao, D. (2011). Optimization and Evaluation of Steel
21 Industry's Water-use System [J]. *Journal of Cleaner Production*, 19(1), 64–69.
- 22 Colla, V., Martino, I., Branca, T. A., Fornai, B., Romaniello, L., & Rosito, F. (2017). Efficient use of water resources
23 in the steel industry. *Water*, 9(11), 874.
- 24 CRH plc. (2023). *Sustainability Report 2023*.
- 25 CSB. (2025). *Kuwait Central Statistical Bureau* [Dataset].
- 26 CSB census. (2005). *Population and Housing Census* [Dataset].
- 27 CSB census. (2011). *Population and Housing Census* [Dataset].
- 28 CSB census. (2021). *Population and Housing Census* [Dataset].



- 1 Dake, L. P. (1983). *Fundamentals of reservoir engineering* (Vol. 8). Elsevier.
2 [https://books.google.com/books?hl=en&lr=&id=mFqpqMA62w8C&oi=fnd&pg=PP1&dq=Dake,+L.+P.+\(](https://books.google.com/books?hl=en&lr=&id=mFqpqMA62w8C&oi=fnd&pg=PP1&dq=Dake,+L.+P.+(1978).+Fundamentals+of+Reservoir+Engineering.+Elsevier.&ots=Fs1lNVnEGi&sig=Mye-gQVdnaRIKDGfUDbrfx4aFA0)
3 [1978\).+Fundamentals+of+Reservoir+Engineering.+Elsevier.&ots=Fs1lNVnEGi&sig=Mye-](https://books.google.com/books?hl=en&lr=&id=mFqpqMA62w8C&oi=fnd&pg=PP1&dq=Dake,+L.+P.+(1978).+Fundamentals+of+Reservoir+Engineering.+Elsevier.&ots=Fs1lNVnEGi&sig=Mye-gQVdnaRIKDGfUDbrfx4aFA0)
4 [gQVdnaRIKDGfUDbrfx4aFA0](https://books.google.com/books?hl=en&lr=&id=mFqpqMA62w8C&oi=fnd&pg=PP1&dq=Dake,+L.+P.+(1978).+Fundamentals+of+Reservoir+Engineering.+Elsevier.&ots=Fs1lNVnEGi&sig=Mye-gQVdnaRIKDGfUDbrfx4aFA0)
5 Dawoud, M. A., Sefelnasr, A., Ebraheem, A. A., Alnaimat, F., Mathew, B., Hamouda, M. A., Hassan, A. A., Zubari,
6 W. K., & Sherif, M. (2024). *Produced Water Treatment and Reuse Options: Alternatives for Sustainable*
7 *Water Resources*. <https://dx.doi.org/10.2118/218959-MS>
8 DESTATIS. (2016). *Water Withdrawal Tables*. [https://www.destatis.de/EN/Themes/Society-](https://www.destatis.de/EN/Themes/Society-Environment/Environment/Material-Energy-Flows/Tables/withdrawal-water.html?view=main[Print])
9 [Environment/Environment/Material-Energy-Flows/Tables/withdrawal-water.html?view=main\[Print\]](https://www.destatis.de/EN/Themes/Society-Environment/Environment/Material-Energy-Flows/Tables/withdrawal-water.html?view=main[Print])
10 DOS. (2025). *Department of Statistics, Hashemite Kingdom of Jordan* [Dataset].
11 DOS census. (1994). *General Population and Housing Census 1994* [Dataset].
12 DOS census. (2004). *General Population and Housing Census 2004* [Dataset].
13 DOS census. (2015). *General Population and Housing Census 2015* [Dataset].
14 Droppers, B., Franssen, W. H. P., van Vliet, M. T. H., Nijssen, B., & Ludwig, F. (2020). Simulating human impacts
15 on global water resources using VIC-5. *Geoscientific Model Development*, 13(10), 5029–5052.
16 <https://doi.org/10.5194/gmd-13-5029-2020>
17 du Plessis, A. (2023). Water Resources from a Global Perspective. In A. du Plessis (Ed.), *South Africa's Water*
18 *Predicament: Freshwater's Unceasing Decline* (pp. 1–25). Springer International Publishing.
19 https://doi.org/10.1007/978-3-031-24019-5_1
20 EGA. (2023). *EGA ESG Sustainability Report 2023*.
21 Ellis, M., Dillich, S., & Margolis, N. (2001). Industrial water use and its energy implications. *Proceedings Of*, 23–34.
22 Esmaeeli, A., & Sarrafzadeh, M.-H. (2023). Reducing freshwater consumption in pulp and paper industries using
23 pinch analysis and mathematical optimization. *Journal of Water Process Engineering*, 53, 103646.
24 EuroStat. (2026). *Eurostat Database* [Dataset]. <https://ec.europa.eu/eurostat/data/database>
25 F. T. Avelino, A., & Dall'ërba, S. (2020). What Factors Drive the Changes in Water Withdrawals in the U.S.
26 Agriculture and Food Manufacturing Industries between 1995 and 2010? *Environmental Science &*
27 *Technology*, 54(17), 10421–10434. <https://doi.org/10.1021/acs.est.9b07071>



- 1 Fadlelmawla, A., & Al-Otaibi, M. (2005). Analysis of the Water Resources Status in Kuwait. *Water Resources*
2 *Management*, 19(5), 555–570. <https://doi.org/10.1007/s11269-005-6810-3>
- 3 FAOSTAT. (2025). *FAOSTAT Forestry Production and Trade Database* [Dataset].
- 4 FCSC. (2025). *UAE Federal Competitiveness and Statistics Centre* [Dataset].
- 5 Flörke, M., Kynast, E., Bärlund, I., Eisner, S., Wimmer, F., & Alcamo, J. (2013). Domestic and industrial water uses
6 of the past 60 years as a mirror of socio-economic development: A global simulation study. *Global*
7 *Environmental Change*, 23(1), 144–156.
- 8 Flörke, M., Schneider, C., & McDonald, R. I. (2018). Water competition between cities and agriculture driven by
9 climate change and urban growth. *Nature Sustainability*, 1(1), 51–58.
- 10 Freije, A. M., Hammad, L. H., Al-Mannai, M., & Perna, S. (2023). Factors Influencing Water Consumption in the
11 Kingdom of Bahrain and Environmental Consequences of Bottled Water Consumption. *Annali Di Igiene,*
12 *Medicina Preventiva e Di Comunita*, 35(1). <https://annali-igiene.it/articoli/2023/1/09-Freije.pdf>
- 13 Frontuto, V., Felici, T., Dalmazzone, S., Falsetti, B., Ignaccolo, R., Laio, F., & Bagliani, M. M. (2025). Unsustainable
14 global freshwater consumption driven by economic growth. *World Development*, 196, 107185.
- 15 Fujimori, S., Hanasaki, N., & Masui, T. (2017). Projections of industrial water withdrawal under shared
16 socioeconomic pathways and climate mitigation scenarios. *Sustainability Science*, 12(2), 275–292.
17 <https://doi.org/10.1007/s11625-016-0392-2>
- 18 Garnier, C., Guiga, W., Lameloise, M.-L., & Fargues, C. (2023). Water reuse in the food processing industries: A
19 review on pressure-driven membrane processes as reconditioning treatments. *Journal of Food Engineering*,
20 344, 111397.
- 21 Garrick, D., De Stefano, L., Yu, W., Jorgensen, I., O'Donnell, E., Turley, L., Aguilar-Barajas, I., Dai, X., de Souza
22 Leão, R., & Punjabi, B. (2019). Rural water for thirsty cities: A systematic review of water reallocation from
23 rural to urban regions. *Environmental Research Letters*, 14(4), 043003.
- 24 GASTAT. (2004). *General Authority for Statistics Saudi Arabia* [Dataset].
- 25 GASTAT. (2010). *General Authority for Statistics Saudi Arabia* [Dataset].
- 26 GASTAT. (2022). *General Authority for Statistics Saudi Arabia* [Dataset].
- 27 GASTAT. (2025). *Saudi Arabia General Authority for Statistics* [Dataset].



- 1 GEM. (2026). *Global Oil and Gas Extraction Tracker (GOGET)* [Map]. Global Energy Monitor.
2 <https://globalenergymonitor.org/projects/global-oil-gas-extraction-tracker/>
- 3 Gharabaghi, S., Stahl, E., & Bonakdari, H. (2019). Integrated nonlinear daily water demand forecast model (case
4 study: City of Guelph, Canada). *Journal of Hydrology*, 579, 124182.
- 5 Gleick, P. H. (2023). Moving to a sustainable future for water. *Nature Water*, 1(6), 486–487.
- 6 Goodwin, S., Carlson, K., Douglas, C., & Knox, K. (2012). Life cycle analysis of water use and intensity of oil and
7 gas recovery in Wattenberg field, Colo. *Oil & Gas Journal*, 110(5), 48–59.
- 8 Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine:
9 Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment, Big Remotely Sensed*
10 *Data: Tools, Applications and Experiences*, 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>
- 11 GPCA. (2015). *Gulf Petrochemicals and Chemicals Association (GPCA) Annual Report*.
- 12 GPCA. (2017). *Gulf Petrochemicals and Chemicals Association (GPCA) Annual Report*.
- 13 GPCA. (2022). *Gulf Petrochemicals and Chemicals Association (GPCA) Annual Report*.
- 14 GRC. (2020). *Kingdom of Saudi Arabia Water Sector Report*. Gulf Research Center.
- 15 Greve, P., Kahil, T., Mochizuki, J., Schinko, T., Satoh, Y., Burek, P., Fischer, G., Tramberend, S., Burtscher, R., &
16 Langan, S. (2018). Global assessment of water challenges under uncertainty in water scarcity projections.
17 *Nature Sustainability*, 1(9), 486–494.
- 18 Guo, G., Liu, S., Wu, Y., Li, J., Zhou, R., & Zhu, X. (2018). Short-Term Water Demand Forecast Based on Deep
19 Learning Method. *Journal of Water Resources Planning and Management*, 144(12), 04018076.
20 [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000992](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000992)
- 21 Guo, X., Wang, A., Liu, G., & Du, B. (2022). Expanded S-Curve Model of Relationship between Domestic Water
22 Usage and Economic Development: A Case Study of Typical Countries. *Applied Sciences*, 12(12).
23 <https://doi.org/10.3390/app12126090>
- 24 Hanasaki, N., Fujimori, S., Yamamoto, T., Yoshikawa, S., Masaki, Y., Hijioka, Y., Kainuma, M., Kanamori, Y.,
25 Masui, T., & Takahashi, K. (2013). A global water scarcity assessment under Shared Socio-economic
26 Pathways–Part 1: Water use. *Hydrology and Earth System Sciences*, 17(7), 2375–2391.



- 1 Hansen, É., Rodrigues, M. A. S., Aragão, M. E., & de Aquim, P. M. (2018). Water and wastewater minimization in a
2 petrochemical industry through mathematical programming. *Journal of Cleaner Production*, 172, 1814–
3 1822.
- 4 Hashemi, F., Young, S., Hashemi, H., Leiviskä, T., Shafea, L., Khedri, M., Borj, B. P., Sayyadi, A., & Hajivand, M.
5 (2024). *Water footprint reduction in oil and gas refineries through water reuse: A systematic review*.
6 https://www.preprints.org/frontend/manuscript/3b2acb64ff7a2b8b2e3653e10d4ddda/download_pub
- 7 He, C., Liu, Z., Wu, J., Pan, X., Fang, Z., Li, J., & Bryan, B. A. (2021). Future global urban water scarcity and potential
8 solutions. *Nature Communications*, 12(1), 4667. <https://doi.org/10.1038/s41467-021-25026-3>
- 9 Hejazi, M., Edmonds, J., Chaturvedi, V., Davies, E., & Eom, J. (2013). Scenarios of global municipal water-use
10 demand projections over the 21st century. *Hydrological Sciences Journal*, 58(3), 519–538.
11 <https://doi.org/10.1080/02626667.2013.772301>
- 12 Hejazi, M., Edmonds, J., Clarke, L., Kyle, P., Davies, E., Chaturvedi, V., Wise, M., Patel, P., Eom, J., & Calvin, K.
13 (2014). Long-term global water projections using six socioeconomic scenarios in an integrated assessment
14 modeling framework. *Technological Forecasting and Social Change*, 81, 205–226.
- 15 Hou, C., Li, Y., Sang, S., Zhao, X., Liu, Y., Liu, Y., & Zhao, F. (2023). High-resolution mapping of monthly industrial
16 water withdrawal in China from 1965 to 2020. *Earth System Science Data Discussions*, 2023, 1–25.
- 17 House-Peters, L. A., & Chang, H. (2011). Urban water demand modeling: Review of concepts, methods, and
18 organizing principles. *Water Resources Research*, 47(5), 2010WR009624.
19 <https://doi.org/10.1029/2010WR009624>
- 20 Huang, Z., Hejazi, M., Li, X., Tang, Q., Vernon, C., Leng, G., Liu, Y., Döll, P., Eisner, S., Gerten, D., Hanasaki, N.,
21 & Wada, Y. (2018). Reconstruction of global gridded monthly sectoral water withdrawals for 1971–2010
22 and analysis of their spatiotemporal patterns. *Hydrology and Earth System Sciences*, 22(4), 2117–2133.
23 <https://doi.org/10.5194/hess-22-2117-2018>
- 24 IEA. (2016). *Water energy nexus—Excerpt from the world energy outlook 2016*. Organisation for Economic Co-
25 Operation and Development/International Energy Agency.
- 26 IEA. (2026). *Electricity Information: Country-level Electricity Generation and Consumption* [Dataset].
27 <https://www.iea.org/data-and-statistics>
- 28 iGA. (2025). *Bahrain Information \& eGovernment Authority* [Dataset].



- 1 iGA census. (1991). *Population, Housing, Buildings and Establishments Census* [Dataset].
- 2 iGA census. (2010). *Population, Housing, Buildings and Establishments Census* [Dataset].
- 3 iGA census. (2020). *Population, Housing, Buildings and Establishments Census* [Dataset].
- 4 InterCement. (2022). *Sustainability Report 2022*.
- 5 Islam, K., Maeno, K., Yokoi, R., Giurco, D., Kagawa, S., Murakami, S., & Motoshita, M. (2025). Geological resource
- 6 production constrained by regional water availability. *Science*, 387(6739), 1214–1218.
- 7 <https://doi.org/10.1126/science.adk5318>
- 8 Japan Statistics. (2019). *CHAPTER 11 ENERGY AND WATER*.
- 9 Jiang, Q., Guo, W., Wang, Z., Wu, Y., Zhao, Y., Tao, M., & Sun, Y. (2024). Forecasting regional water demand using
- 10 multi-fidelity data and harris hawks optimization of generalized regression neural network models—A case
- 11 study of Heilongjiang Province, China. *Journal of Hydrology*, 634, 131084.
- 12 Jiao, Y.-J., Jiang, K.-J., Chen, S., Xiang, P.-P., & He, C.-M. (2024). Water use in the industrial sector based on the
- 13 IPAC model under the carbon-neutral transformation path in China. *Advances in Climate Change Research*,
- 14 15(6), 1130–1146.
- 15 Jones, L. E., & Olsson, G. (2017). Solar Photovoltaic and Wind Energy Providing Water. *Global Challenges*, 1(5),
- 16 1600022. <https://doi.org/10.1002/gch2.201600022>
- 17 Joseph, N., Ryu, D., Malano, H. M., George, B., & Sudheer, K. P. (2019). Estimation of industrial water demand in
- 18 India using census-based statistical data. *Resources, Conservation and Recycling*, 149, 31–44.
- 19 Kahil, T., Baccour, S., Joseph, J., Sahu, R., Burek, P., Ng, J. Y., Asad, S., Fridman, D., Albiac, J., Ward, F. A., &
- 20 Wada, Y. (2025). Development of the global hydro-economic model (ECHO-Global version 1.0) for
- 21 assessing the performance of water management options. *Geoscientific Model Development*, 18(20), 7987–
- 22 8015. <https://doi.org/10.5194/gmd-18-7987-2025>
- 23 Kalifa, A., Al-Maadid, A., Koutiva, I., & Makropoulos, C. (2021). Individual water consumption behavior in relation
- 24 to urban residential dynamics: The Case of Qatar. *Urban Water Journal*, 18(10), 806–816.
- 25 <https://doi.org/10.1080/1573062X.2021.1941135>
- 26 Kamali, M., & Khodaparast, Z. (2015). Review on recent developments on pulp and paper mill wastewater treatment.
- 27 *Ecotoxicology and Environmental Safety*, 114, 326–342. <https://doi.org/10.1016/j.ecoenv.2014.05.005>
- 28 KAPSARC. (2022). *Oil refinery throughput 1980–2020*.



- 1 KAPSARC. (2025). *Mineral Ores Extracted*. [https://datasource.kapsarc.org/explore/assets/saudi-arabia-mineral-ores-](https://datasource.kapsarc.org/explore/assets/saudi-arabia-mineral-ores-extracted-2004-2013/)
2 [extracted-2004-2013/](https://datasource.kapsarc.org/explore/assets/saudi-arabia-mineral-ores-extracted-2004-2013/)
- 3 KAPSARC. (2026a). *Metal Production Data* [Dataset].
4 [https://datasource.kapsarc.org/explore/?sort=modified&refine.theme=Minerals&orderBy=updated_at+DES](https://datasource.kapsarc.org/explore/?sort=modified&refine.theme=Minerals&orderBy=updated_at+DESC)
5 [C](https://datasource.kapsarc.org/explore/?sort=modified&refine.theme=Minerals&orderBy=updated_at+DESC)
- 6 KAPSARC. (2026b). *World Oil Production* [Dataset]. [https://datasource.kapsarc.org/explore/assets/world-oil-](https://datasource.kapsarc.org/explore/assets/world-oil-production/)
7 [production/](https://datasource.kapsarc.org/explore/assets/world-oil-production/)
- 8 Kassab, M. A., Abbas, A. E., Elgamal, I., Shawky, B. M., Mubarak, M. F., & Hosny, R. (2021). *Review on the*
9 *estimating the effective way for managing the produced water: Case study.*
10 <https://www.cabidigitallibrary.org/doi/full/10.5555/20210362519>
- 11 Khafajah, H. I., Abdelsamie, M. M., & Ali, M. I. H. (2026). Thermoeconomic assessment of a cement-plant waste-
12 heat-driven trigeneration system for power, cooling, and desalination. *Energy Nexus*, 21, 100631.
13 <https://doi.org/10.1016/j.nexus.2026.100631>
- 14 Khan, Z., Thompson, I., Vernon, C. R., Graham, N. T., Wild, T. B., & Chen, M. (2023). Global monthly sectoral water
15 use for 2010–2100 at 0.5° resolution across alternative futures. *Scientific Data*, 10(1), 201.
16 <https://doi.org/10.1038/s41597-023-02086-2>
- 17 Kizhisseri, M. I., Mohamed, M. M., El-Shorbagy, W., Chowdhury, R., & McDonald, A. (2021). Development of a
18 dynamic water budget model for Abu Dhabi Emirate, UAE. *PLOS ONE*, 16(1), e0245140.
19 <https://doi.org/10.1371/journal.pone.0245140>
- 20 Kotagama, H., Zekri, S., Al Harthi, R., & Boughanmi, H. (2017). Demand function estimate for residential water in
21 Oman. *International Journal of Water Resources Development*, 33(6), 907–916.
22 <https://doi.org/10.1080/07900627.2016.1238342>
- 23 LafargeHolcim. (2022). *Sustainability Report 2022*.
- 24 Lake, L., Johns, R. T., Rossen, W. R., & Pope, G. A. (2014). *Fundamentals of Enhanced Oil Recovery*.
25 <https://onepetro.org/books/book/41/Fundamentals-of-Enhanced-Oil-Recovery>
- 26 Lenzen, M., Geschke, A., Abd Rahman, M. D., Xiao, Y., Fry, J., Reyes, R., Dietzenbacher, E., Inomata, S., Kanemoto,
27 K., Los, B., Moran, D., Schulte In Den Bäumen, H., Tukker, A., Walmsley, T., Wiedmann, T., Wood, R., &



- 1 Yamano, N. (2017). The Global MRIO Lab – charting the world economy. *Economic Systems Research*,
2 29(2), 158–186. <https://doi.org/10.1080/09535314.2017.1301887>
- 3 Lenzen, M., Geschke, A., West, J., Fry, J., Malik, A., Giljum, S., Milà i Canals, L., Piñero, P., Lutter, S., Wiedmann,
4 T., Li, M., Sevenster, M., Potočník, J., Teixeira, I., Van Voore, M., Nansai, K., & Schandl, H. (2022).
5 Implementing the material footprint to measure progress towards Sustainable Development Goals 8 and 12.
6 *Nature Sustainability*, 5(2), 157–166. <https://doi.org/10.1038/s41893-021-00811-6>
- 7 Li, M., Tong, Y., Zhu, J., & Xu, S. (2024). A high-resolution multi-scale industrial water use dataset in China.
8 *Scientific Data*, 11(1), 1327. <https://doi.org/10.1038/s41597-024-04204-0>
- 9 Li, S., Feng, Q., Zhang, X., Yu, C., & Huang, Y. (2023). A new water flooding characteristic curve at ultra-high water
10 cut stage. *Journal of Petroleum Exploration and Production Technology*, 13(1), 101–110.
11 <https://doi.org/10.1007/s13202-022-01538-6>
- 12 Ling, M., Yang, Y., Li, S., & Lv, C. (2023). Evolution and driving forces of water use structures in China. *Journal of*
13 *Cleaner Production*, 427, 139263. <https://doi.org/10.1016/j.jclepro.2023.139263>
- 14 Lohrmann, A., Farfan, J., Caldera, U., Lohrmann, C., & Breyer, C. (2019). Global scenarios for significant water use
15 reduction in thermal power plants based on cooling water demand estimation using satellite imagery. *Nature*
16 *Energy*, 4(12), 1040–1048. <https://doi.org/10.1038/s41560-019-0501-4>
- 17 Lohrmann, A., Lohrmann, C., & Luukka, P. (2022). Global and regional models for identification of cooling
18 technology in thermal power generation for water demand estimations in water-energy nexus studies. *Journal*
19 *of Cleaner Production*, 380, 134842. <https://doi.org/10.1016/j.jclepro.2022.134842>
- 20 Long, H., Xie, R., Gao, C., Sun, M., & Su, B. (2022). Analysis of China’s regional differences in water consumption
21 based on spatial structural decomposition analysis model. *Science of The Total Environment*, 848, 157629.
22 <https://doi.org/10.1016/j.scitotenv.2022.157629>
- 23 LyondellBasell. (2020). *LYB Sustainability Report*. <https://www.lyondellbasell.com/en/sustainability/reporting/>
- 24 LyondellBasell. (2021). *LYB Sustainability Report*. <https://www.lyondellbasell.com/en/sustainability/reporting/>
- 25 LyondellBasell. (2022). *LYB Sustainability Report*. <https://www.lyondellbasell.com/en/sustainability/reporting/>
- 26 LyondellBasell. (2023). *LYB Sustainability Report*. <https://www.lyondellbasell.com/en/sustainability/reporting/>
- 27 MAADEN. (2024). *Ma’aden (Saudi Arabian Mining Company)*.



- 1 Macknick, J., Newmark, R., Heath, G., & Hallett, K. C. (2012). Operational water consumption and withdrawal factors
2 for electricity generating technologies: A review of existing literature. *Environmental Research Letters*, 7(4),
3 045802. <https://doi.org/10.1088/1748-9326/7/4/045802>
- 4 Maus, V., Giljum, S., Gutschlhofer, J., da Silva, D. M., Probst, M., Gass, S. L. B., Luckeneder, S., Lieber, M., &
5 McCallum, I. (2020). A global-scale data set of mining areas. *Scientific Data*, 7(1), 289.
6 <https://doi.org/10.1038/s41597-020-00624-w>
- 7 Maußner, C., Oberascher, M., Autengruber, A., Kahl, A., & Sitzenfrei, R. (2025). Explainable artificial intelligence
8 for reliable water demand forecasting to increase trust in predictions. *Water Research*, 268, 122779.
9 <https://doi.org/10.1016/j.watres.2024.122779>
- 10 McCain, W. D. (1990). *The Properties of Petroleum Fluids* (2nd ed.).
- 11 McCain, W. D., Jr. (1991). Reservoir-Fluid Property Correlations—State of the Art. *SPE Reservoir Engineering*,
12 6(02), 266–272. <https://doi.org/10.2118/18571-PA>
- 13 Meißner, S. (2021). The Impact of Metal Mining on Global Water Stress and Regional Carrying Capacities—A GIS-
14 Based Water Impact Assessment. *Resources*, 10(12). <https://doi.org/10.3390/resources10120120>
- 15 Meng, X., & Wu, L. (2021). Prediction of per capita water consumption for 31 regions in China. *Environmental*
16 *Science and Pollution Research*, 28(23), 29253–29264. <https://doi.org/10.1007/s11356-021-12368-0>
- 17 Miao, Z. (2025). Oil dependency and democratic outcomes in the Middle East: A comparative analysis of resource-
18 rich and resource-scarce states. *International Politics*. <https://doi.org/10.1057/s41311-025-00693-x>
- 19 Mohamed, M. M., & Al-Mualla, A. A. (2010). Water demand forecasting in Umm Al-Quwain using the constant rate
20 model. *Desalination*, 259(1), 161–168. <https://doi.org/10.1016/j.desal.2010.04.014>
- 21 Morain, A., Ilangovan, N., Delhom, C., & Anandhi, A. (2024). Artificial Intelligence for Water Consumption
22 Assessment: State of the Art Review. *Water Resources Management*, 38(9), 3113–3134.
23 <https://doi.org/10.1007/s11269-024-03823-x>
- 24 Müller Schmied, H., Cáceres, D., Eisner, S., Flörke, M., Herbert, C., Niemann, C., Peiris, T. A., Popat, E., Portmann,
25 F. T., Reinecke, R., Schumacher, M., Shadkam, S., Telteu, C.-E., Trautmann, T., & Döll, P. (2021). The
26 global water resources and use model WaterGAP v2.2d: Model description and evaluation. *Geoscientific*
27 *Model Development*, 14(2), 1037–1079. <https://doi.org/10.5194/gmd-14-1037-2021>



- 1 Nath, F., Chowdhury, M. O. S., & Rhaman, M. M. (2023). Navigating Produced Water Sustainability in the Oil and
2 Gas Sector: A Critical Review of Reuse Challenges, Treatment Technologies, and Prospects Ahead. *Water*,
3 15(23). <https://doi.org/10.3390/w15234088>
- 4 Nazemi, A., & Wheater, H. S. (2015). On inclusion of water resource management in Earth system models –
5 Part 1: Problem definition and representation of water demand. *Hydrology and Earth System Sciences*, 19(1),
6 33–61. <https://doi.org/10.5194/hess-19-33-2015>
- 7 NCSI. (2025). *Oman National Centre for Statistics and Information* [Dataset].
- 8 NCSI census. (1993). *Population, Housing and Establishments Census 1993* [Dataset].
- 9 NCSI census. (2003). *Population, Housing and Establishments Census 2003* [Dataset].
- 10 NCSI census. (2010). *Population, Housing and Establishments Census 2010* [Dataset].
- 11 NCSI census. (2020). *Population, Housing and Establishments Census 2020* [Dataset].
- 12 OECD. (2018, June 26). *Purchasing Power Parities for cross-country productivity comparisons: OECD Compendium*
13 *of Productivity Indicators 2018*. OECD. [https://www.oecd.org/en/publications/oecd-compendium-of-](https://www.oecd.org/en/publications/oecd-compendium-of-productivity-indicators-2018_pdtvy-2018-en/full-report/component-41.html)
14 [productivity-indicators-2018_pdtvy-2018-en/full-report/component-41.html](https://www.oecd.org/en/publications/oecd-compendium-of-productivity-indicators-2018_pdtvy-2018-en/full-report/component-41.html)
- 15 Oki, T., & Kanae, S. (2006). Global Hydrological Cycles and World Water Resources. *Science*, 313(5790), 1068–
16 1072. <https://doi.org/10.1126/science.1128845>
- 17 Olejnik, K. (2011). Water Consumption in Paper Industry – Reduction Capabilities and the Consequences. In A. T.
18 Atimtay & S. K. Sikdar (Eds.), *Security of Industrial Water Supply and Management* (pp. 113–129). Springer
19 Netherlands. https://doi.org/10.1007/978-94-007-1805-0_8
- 20 OWID. (2026a). *Total electricity generation* [Dataset]. [https://archive.ourworldindata.org/20260304-](https://archive.ourworldindata.org/20260304-094028/grapher/electricity-generation.html)
21 [094028/grapher/electricity-generation.html](https://archive.ourworldindata.org/20260304-094028/grapher/electricity-generation.html)
- 22 OWID. (2026b). *Total energy use* [Dataset]. <https://ourworldindata.org/energy>
- 23 PIC. (2014). *PIC Sustainability Report 2013–2014*. [https://www.pic.com.kw/wp-content/uploads/2021/01/PIC-](https://www.pic.com.kw/wp-content/uploads/2021/01/PIC-SustainabilityBrochure2_v21_HR_2013-2014.pdf)
24 [SustainabilityBrochure2_v21_HR_2013-2014.pdf](https://www.pic.com.kw/wp-content/uploads/2021/01/PIC-SustainabilityBrochure2_v21_HR_2013-2014.pdf)
- 25 Pokhrel, Y., Felfelani, F., Satoh, Y., Boulange, J., Burek, P., Gädeke, A., Gerten, D., Gosling, S. N., Grillakis, M.,
26 Gudmundsson, L., Hanasaki, N., Kim, H., Koutroulis, A., Liu, J., Papadimitriou, L., Schewe, J., Müller
27 Schmied, H., Stacke, T., Telteu, C.-E., ... Wada, Y. (2021). Global terrestrial water storage and drought



- 1 severity under climate change. *Nature Climate Change*, 11(3), 226–233. [https://doi.org/10.1038/s41558-020-](https://doi.org/10.1038/s41558-020-00972-w)
2 00972-w
- 3 PSA. (2025). *Qatar Planning and Statistics Authority* [Dataset].
- 4 PSA census. (1986). *Population, Housing and Establishments Census* [Dataset].
- 5 PSA census. (1997). *Population, Housing and Establishments Census* [Dataset].
- 6 PSA census. (2004). *Population, Housing and Establishments Census* [Dataset].
- 7 PSA census. (2010). *Population, Housing and Establishments Census* [Dataset].
- 8 PSA census. (2020). *Population, Housing and Establishments Census* [Dataset].
- 9 QAPCO. (2023). *QAPCO Integrated Report 2023*. [https://qapco.com/storage/2024/06/QAPCO-Integrated-Report-](https://qapco.com/storage/2024/06/QAPCO-Integrated-Report-2023-.pdf)
10 2023-.pdf
- 11 Ren, D., Mao, H., Xiao, D., Lu, Y., Xu, X., Ma, Q., & Wang, L. (2025). Dietary differences amplify the water stress
12 impacts of virtual water trade in the yellow river basin. *Scientific Reports*, 15(1), 44370.
13 <https://doi.org/10.1038/s41598-025-28020-7>
- 14 Reynolds, J. F., Smith, D. M. S., Lambin, E. F., Turner, B. L., Mortimore, M., Batterbury, S. P. J., Downing, T. E.,
15 Dowlatabadi, H., Fernández, R. J., Herrick, J. E., Huber-Sannwald, E., Jiang, H., Leemans, R., Lynam, T.,
16 Maestre, F. T., Ayarza, M., & Walker, B. (2007). Global Desertification: Building a Science for Dryland
17 Development. *Science*, 316(5826), 847–851. <https://doi.org/10.1126/science.1131634>
- 18 Rosa, L., & Sangiorgio, M. (2025). Global water gaps under future warming levels. *Nature Communications*, 16(1),
19 1192. <https://doi.org/10.1038/s41467-025-56517-2>
- 20 SABIC. (2022). *SABIC Sustainability Report 2022*.
- 21 Schiavina, M., Freire, S., Alessandra, C., & MacManus, K. (2023). *GHSL data package 2023*. Publications Office.
22 <https://data.europa.eu/doi/10.2760/20212>
- 23 Sharma, N., Lemar, P., & Nimbalkar, S. (2025). Opportunities for iron and steel industrial wastewater treatment and
24 reuse in the United States. *Water Resources and Industry*, 34, 100298.
25 <https://doi.org/10.1016/j.wri.2025.100298>
- 26 Shen YanJun, S. Y., Oki, T., Utsumi, N., Kanae, S., & Hanasaki, N. (2008). *Projection of future world water resources*
27 *under SRES scenarios: Water withdrawal*. <https://www.cabidigitallibrary.org/doi/full/10.5555/20083064366>



- 1 Shrestha, M., Manandhar, S., & Shrestha, S. (2020). Forecasting water demand under climate change using artificial
2 neural network: A case study of Kathmandu Valley, Nepal. *Water Supply*, 20(5), 1823–1833.
3 <https://doi.org/10.2166/ws.2020.090>
- 4 Shu, J., Xia, X., Han, S., He, Z., Pan, K., & Liu, B. (2024). Long-term water demand forecasting using artificial
5 intelligence models in the Tuojiang River basin, China. *PLOS ONE*, 19(5), e0302558.
6 <https://doi.org/10.1371/journal.pone.0302558>
- 7 Skinner, K. D., Niswonger, R. G., Harris, M. A., McCarthy, B. A., Chamberlin, C., Lombard, M. A., Diehl, T. H.,
8 Galanter, A. E., Gorman-Sanisaca, L. E., & Stewart, J. S. (2025). Water Withdrawal and Consumption Trends
9 for Thermoelectric-Power Plants in the Conterminous United States, 2008–2020. *ACS ES&T Water*, 5(10),
10 5820–5831. <https://doi.org/10.1021/acsestwater.5c00360>
- 11 Su, Q., & Karthikeyan, R. (2023). Regional Water Stress Forecasting: Effects of Climate Change, Socioeconomic
12 Development, and Irrigated Agriculture—A Texas Case Study. *Sustainability*, 15(12).
13 <https://doi.org/10.3390/su15129290>
- 14 Sun, P., Elgowainy, A., Wang, M., Han, J., & Henderson, R. J. (2018). Estimation of U.S. refinery water consumption
15 and allocation to refinery products. *Fuel*, 221, 542–557. <https://doi.org/10.1016/j.fuel.2017.07.089>
- 16 Suvio, P., Van Hoorn, A., Szabo, M., & Ekdahl, Å. (2012). Water management for sustainable steel industry.
17 *Ironmaking & Steelmaking*, 39(4), 263–269. <https://doi.org/10.1179/030192311X13135947813898>
- 18 Terrapon-Pfaff, J. C., Ortiz, W., Viebahn, P., Kynast, E., & Flörke, M. (2020). Water Demand Scenarios for Electricity
19 Generation at the Global and Regional Levels. *Water*, 12(9). <https://doi.org/10.3390/w12092482>
- 20 Tong, Y., Zhang, Q., Cai, J., Gao, C., Wang, L., & Li, P. (2018). Water consumption and wastewater discharge in
21 China's steel industry. *Ironmaking & Steelmaking*, 45(10), 868–877.
22 <https://doi.org/10.1080/03019233.2018.1538180>
- 23 UAE. (2024). *Operation 300bn, the UAE's industrial strategy | The Official Platform of the UAE Government*.
24 [https://u.ae/en/about-the-uae/strategies-initiatives-and-awards/strategies-plans-and-visions/industry-](https://u.ae/en/about-the-uae/strategies-initiatives-and-awards/strategies-plans-and-visions/industry-science-and-technology/the-uae-industrial-strategy)
25 [science-and-technology/the-uae-industrial-strategy](https://u.ae/en/about-the-uae/strategies-initiatives-and-awards/strategies-plans-and-visions/industry-science-and-technology/the-uae-industrial-strategy)
- 26 Ulusoy, A.-J., Jara-Arriagada, C., Liu, Y., Jenks, B., & Stoianov, I. (2024). Interpretable AI for Short-Term Water
27 Demand Forecasting. *Engineering Proceedings*, 69(1). <https://doi.org/10.3390/engproc2024069101>



- 1 UN-WLC. (2025). *United Nations Water Learning Center (UN-WLC) of the Arab Region at the Arabian Gulf*
2 *University (AGU) in "Integrated Water Resources Management (IWRM)" Diploma Program: Students*
3 *Graduates & Abstracts Book.*
- 4 US Census Bureau. (2025). *Population Estimates* [Dataset]. <https://www.census.gov/programs-surveys/popest.html>
- 5 USGS. (1996). *Cement Statistics and Information | U.S. Geological Survey* [Dataset].
6 <https://www.usgs.gov/centers/national-minerals-information-center/cement-statistics-and-information>
- 7 USGS. (2000). *Cement Statistics and Information | U.S. Geological Survey* [Dataset].
8 <https://www.usgs.gov/centers/national-minerals-information-center/cement-statistics-and-information>
- 9 USGS. (2005). *Cement Statistics and Information | U.S. Geological Survey* [Dataset].
10 <https://www.usgs.gov/centers/national-minerals-information-center/cement-statistics-and-information>
- 11 USGS. (2010). *Cement Statistics and Information | U.S. Geological Survey* [Dataset].
12 <https://www.usgs.gov/centers/national-minerals-information-center/cement-statistics-and-information>
- 13 USGS. (2015). *Cement Statistics and Information | U.S. Geological Survey* [Dataset].
14 <https://www.usgs.gov/centers/national-minerals-information-center/cement-statistics-and-information>
- 15 USGS. (2020). *Cement Statistics and Information | U.S. Geological Survey* [Dataset].
16 <https://www.usgs.gov/centers/national-minerals-information-center/cement-statistics-and-information>
- 17 USGS. (2025). *Cement Statistics and Information | U.S. Geological Survey* [Dataset].
18 <https://www.usgs.gov/centers/national-minerals-information-center/cement-statistics-and-information>
- 19 Van Vliet, M. T., Flörke, M., & Wada, Y. (2017). Quality matters for water scarcity. *Nature Geoscience*, 10(11), 800–
20 802.
- 21 Vanham, D., Gawlik, B. M., & Bidoglio, G. (2017). Food consumption and related water resources in Nordic cities.
22 *Ecological Indicators*, 74, 119–129. <https://doi.org/10.1016/j.ecolind.2016.11.019>
- 23 Veil, J. A., Puder, M. G., Elcock, D., & Redwick, R. J. (2004). *A White Paper Describing Produced Water from*
24 *Production of Crude Oil, Natural Gas, and Coal Bed Methane*. U.S. Department of Energy, National Energy
25 Technology Laboratory.
- 26 Veldkamp, T. I. E., Wada, Y., Aerts, J. C. J. H., Döll, P., Gosling, S. N., Liu, J., Masaki, Y., Oki, T., Ostberg, S.,
27 Pokhrel, Y., Satoh, Y., Kim, H., & Ward, P. J. (2017). Water scarcity hotspots travel downstream due to



- 1 human interventions in the 20th and 21st century. *Nature Communications*, 8(1), 15697.
2 <https://doi.org/10.1038/ncomms15697>
- 3 Wada, Y., & Bierkens, M. F. (2014). Sustainability of global water use: Past reconstruction and future projections.
4 *Environmental Research Letters*, 9(10), 104003.
- 5 Wada, Y., Flörke, M., Hanasaki, N., Eisner, S., Fischer, G., Tramberend, S., Satoh, Y., van Vliet, M. T. H., Yillia, P.,
6 Ringler, C., Burek, P., & Wiberg, D. (2016). Modeling global water use for the 21st century: The Water
7 Futures and Solutions (WFaS) initiative and its approaches. *Geoscientific Model Development*, 9(1), 175–
8 222. <https://doi.org/10.5194/gmd-9-175-2016>
- 9 Wada, Y., van Beek, L. P. H., Viviroli, D., Dürr, H. H., Weingartner, R., & Bierkens, M. F. P. (2011). Global monthly
10 water stress: 2. Water demand and severity of water stress. *Water Resources Research*, 47(7).
11 <https://doi.org/10.1029/2010WR009792>
- 12 Wang, T., Liu, B., Sha, J., Wang, W., You, J., & Zhang, D. (2024). *Multiscale Water Use Driving Effects and Dynamic*
13 *Water Demand Research Based on the Kaya-Lmdi-Stirpat Model* (SSRN Scholarly Paper 4845075). Social
14 Science Research Network. <https://doi.org/10.2139/ssrn.4845075>
- 15 World Bank. (2024). *World Development Indicators: Population, total* [Dataset].
16 <https://data.worldbank.org/indicator/SP.POP.TOTL>
- 17 World Bank. (2026a). *Energy use (kg of oil equivalent per capita)* [Dataset].
18 <https://data.worldbank.org/indicator/EG.USE.PCAP.KG.OE>
- 19 World Bank. (2026b). *World Development Indicators Metadata Glossary: Municipal water withdrawal as a*
20 *percentage of total water withdrawal*. [https://databank.worldbank.org/metadataglossary/world-](https://databank.worldbank.org/metadataglossary/world-development-indicators/series/ER.H2O.FWDM.ZS)
21 [development-indicators/series/ER.H2O.FWDM.ZS](https://databank.worldbank.org/metadataglossary/world-development-indicators/series/ER.H2O.FWDM.ZS)
- 22 World Steel. (2015). *WATER MANAGEMENT IN THE STEEL INDUSTRY worldsteel position paper*—Google
23 *Search*.
24 [https://www.google.com/search?q=WATER+MANAGEMENT+IN+THE+STEEL+INDUSTRY+worldsteel](https://www.google.com/search?q=WATER+MANAGEMENT+IN+THE+STEEL+INDUSTRY+worldsteel+position+paper&rlz=1C1GCEA_enSA1084SA1085&oq=WATER+MANAGEMENT+IN+THE+STEEL+INDUSTRY+worldsteel+position+paper&gs_lcrp=EgZjaHJvbWUyBggAEEUYOTIHCAEQIRiPAjIHCAIQIRiPAtIBBzQyNmowajeoAgCwAgA&sourceid=chrome&ie=UTF-8)
25 [el+position+paper&rlz=1C1GCEA_enSA1084SA1085&oq=WATER+MANAGEMENT+IN+THE+STEEL](https://www.google.com/search?q=WATER+MANAGEMENT+IN+THE+STEEL+INDUSTRY+worldsteel+position+paper&rlz=1C1GCEA_enSA1084SA1085&oq=WATER+MANAGEMENT+IN+THE+STEEL+INDUSTRY+worldsteel+position+paper&gs_lcrp=EgZjaHJvbWUyBggAEEUYOTIHCAEQIRiPAjIHCAIQIRiPAtIBBzQyNmowajeoAgCwAgA&sourceid=chrome&ie=UTF-8)
26 [L+INDUSTRY+worldsteel+position+paper&gs_lcrp=EgZjaHJvbWUyBggAEEUYOTIHCAEQIRiPAjIH](https://www.google.com/search?q=WATER+MANAGEMENT+IN+THE+STEEL+INDUSTRY+worldsteel+position+paper&rlz=1C1GCEA_enSA1084SA1085&oq=WATER+MANAGEMENT+IN+THE+STEEL+INDUSTRY+worldsteel+position+paper&gs_lcrp=EgZjaHJvbWUyBggAEEUYOTIHCAEQIRiPAjIHCAIQIRiPAtIBBzQyNmowajeoAgCwAgA&sourceid=chrome&ie=UTF-8)
27 [CAIQIRiPAtIBBzQyNmowajeoAgCwAgA&sourceid=chrome&ie=UTF-8](https://www.google.com/search?q=WATER+MANAGEMENT+IN+THE+STEEL+INDUSTRY+worldsteel+position+paper&rlz=1C1GCEA_enSA1084SA1085&oq=WATER+MANAGEMENT+IN+THE+STEEL+INDUSTRY+worldsteel+position+paper&gs_lcrp=EgZjaHJvbWUyBggAEEUYOTIHCAEQIRiPAjIHCAIQIRiPAtIBBzQyNmowajeoAgCwAgA&sourceid=chrome&ie=UTF-8)



- 1 Yang, C., Meng, J., Liu, B., Wang, Z., & Wang, K. (2024). A Water Demand Forecasting Model Based on Generative
2 Adversarial Networks and Multivariate Feature Fusion. *Water*, 16(12). <https://doi.org/10.3390/w16121731>
- 3 Zarei, S., Bozorg-Haddad, O., Nikoo, M. R., & Loáiciga, H. A. (2025). A disaggregated system dynamics and agent-
4 based modeling of the water-energy-food nexus for optimizing water allocation. *Scientific Reports*, 15(1),
5 34973.
- 6 Zhang, X., Evans, J. P., & Burrell, A. L. (2024). Less than 4% of dryland areas are projected to desertify despite
7 increased aridity under climate change. *Communications Earth & Environment*, 5(1), 300.
8 <https://doi.org/10.1038/s43247-024-01463-y>
- 9 Zhu, X., Hou, M., & Wei, J. (2024). Global Water Use and Its Changing Patterns: Insights from OECD Countries.
10 *Water*, 16(24). <https://doi.org/10.3390/w16243592>
- 11