Towards Water Positive: Developing a Method to Assess Embodied Water in Electricity Purchased by LinkedIn

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Table of Contents

Executive Summary **3**
PART I: Project Background **4**
1.1 Scope 5
1.2 Literature Review 6
1.2.1 Water accounting and report 6
1.2.2 Water Scarcity Method 7
PART II: Methodology **8**
2.1 LinkedIn Data Set 8
2.2 Tools For Data Analysis 9
2.2.1 Water IMPACT Tool 9
2.2.2 Aqueduct 4.0 13
2.2.3 AWARE 2.0 17
PART IV: Results **21**
4.1 Summary of Results 21
4.2 WIT - Electricity-related Water Volume 22
4.2.1 Estimate of LinkedIn's Scope 2 Water Consumption and Water Withdrawal by Facility Type 22
4.2.2 Estimate of Water Consumption and Water Withdrawal by eGRID 23
4.3 AWARE 2.0 - Weighted Water Consumption and Withdrawal 26
4.4 Aqueduct 4.0 - Estimating Regional Water Stress Level 29
4.4.1 Facility-level Water Stress 29
4.4.2 Plant-Level Weighted Water Stress Distribution 30
4.4.3 eGRID-Level Water Stress and Water Consumption 32
4.4.4 eGRID-Level Water Stress and Water Withdrawal 34
PART V: Discussion **37**
5.1 Model Recommendations 37
5.1.1 Analysis of Model Differences 37
5.2 Alternative Approaches; Plant-level Estimates and Modeling in LinkedIn's Scope 2 Water Use Beyond the USA 39
5.3 Towards Water Positivity → High-Level Recommendations 40
5.4 Limitations and Future Research 40
PART VI: Conclusion **42**
Appendices **43**
REFERENCES **50**

Executive Summary

LinkedIn aims to be water positive by 2030. Watersheds are under increasing stress globally necessitating the need for more responsible stewardship of this resource by industry, governments, and individuals. Water consumption to meet the energy demands of the tech sector, particularly from the growth of data centers, presents a challenge in this regard. LinkedIn aims to assess their embodied water in their purchased electricity (i.e., Scope 2 water use) to track their water use impacts and continue their journey towards becoming water positive. We developed a methodology utilizing the Berkley Laboratory Water Impact Tool to estimate LinkedIn's domestic Scope 2 water withdrawal and consumption (water withdrawn but not returned to surface water). We also clarified water stress from LinkedIn's purchased energy using two methods, AWARE 2.0 and the Aqueduct 4.0 tool. Using geospatial data and mapping software we mapped LinkedIn's Scope 2 water footprint across the United States and identified which electrical grids are impact hotspots. We find that the ERCT (Texas) and SRVC (the Carolinas) electrical grids exhibit the highest water withdrawal, while the NWPP (Northwest) has the highest water consumption. The highest water stress region for both Aqueduct and AWARE 2.0 is CAMX (California). Our method lays the foundation for additional Scope 2 water assessments across LinkedIn's global portfolio of facilities. To aid in this, we developed statistical models of plant-level water consumption as a surrogate to estimate water use in regions lacking analogs to the Water Impact Tool. In addition to considering their Scope 2 water use, we propose that LinkedIn estimate their Scope 3 water usage since Semiconductor chip manufacturing is extremely water intensive. This project is a stepping stone to reaching LinkedIn's water positive goals for the future. By embracing this challenge, LinkedIn has the potential to be a sustainability leader in the tech sector.

PART I: Project Background

According to LinkedIn, being water positive means decreasing the water intensity of the facilities, including data center, Pops, and offices and replenishing more water than consumed. LinkedIn was acquired by Microsoft in 2016 necessitating alignment of LinkedIn's sustainability goals with Microsoft's. Initially, LinkedIn tracks their direct water use annually including their data center, campuses and cafeterias. Their water positivity commitment has five components to it: reduction, replenishment, accessibility, digitization, and policy.
These five components provide a holistic framework for assessing direct and indirect water impacts. Reduction focuses on lowering direct water use. Replenishment aims to restore more water than is consumed, particularly in high-stress basins. Accessibility seeks to provide 1.5 million people across 18 priority basins with access to clean water and sanitation. Digitization supports innovation in water data, monitoring, and related technologies. Policy emphasizes advocacy for public policies that improve the access, quantity, and quality of water needed by both humans and ecosystems.As water scarcity challenges become increasingly significant, LinkedIn recognized the importance of expanding its accounting to include indirect water use from Scope 2 purchased electricity. As they strive to go beyond LinkedIn's current commitment of being water positive by 203.

71% of Earth's surface is covered by water, 97% of which is saltwater and only 3% is freshwater. This water is used by eight billion people in the world for agriculture, industry and everyday needs. So the real quantity they get is less than 1% (World Health Organization,2025) . One of the United Nations Sustainable Development Goals (SDGs) is getting access to clean drinking water. As the world's awareness of sustainability grows, it also increases awareness of the water scarcity problem. This is more critical in regions that are facing water stress. Competition for limited supplies of water is increasing in areas where populations, agricultural demands or climate patterns are changing. If the electricity used to power data centers is sourced from water-intensive energy sources in these stressed regions, it may increase local water scarcity and cause risks to both ecosystems and communities.Therefore, understanding these indirect impacts is critical for companies seeking to build more sustainable operations.

Data centers electricity usage increased from 58 TWh in 2014 to 176 TWh in 2023 and will become more numerous around the country, according to estimates and keep climbing between 325 to 580 TWh by 2028 (Shehabi et al.,2024). They require large amounts of electricity to power servers, cooling systems, and other infrastructure. While much attention has been given to the greenhouse gas emissions associated with this energy use, less focus has been placed on the water consumed during electricity production. In many parts of the world, large volumes of freshwater are used at power plants for cooling and steam generation. The energy sector accounts for roughly 10% of global freshwater withdrawals, and in the United States thermoelectric power which withdraws the largest water sector, accounting for 41% of total water withdrawals in 2015 (IEA, n.d.). This means that even though data centers may not directly use much water on–site, their electricity demand can contribute to substantial indirect water withdrawals and consumption.

In order to mitigate these environmental impacts, LinkedIn has committed to becoming water positive by 2030. Being water positive means that the company is aiming to reduce its operational water use. This commitment involves reducing water use, improving efficiency, and investing in projects that restore or replenish water sources, like wetland restoration or watershed protection. By taking responsibility for both direct and indirect water impacts, LinkedIn is demonstrating its intent to play a leadership role in corporate sustainability.

Our project's main goal is to assess the indirect water embodied in purchased electricity for LinkedIn. Embodied water refers to the volume of water withdrawn and consumed across an organization's full value chain. Our main focus was on LinkedIn's Scope 2 water use from purchased energy, specifically to help LinkedIn understand how and where to integrate water positive strategies into its decision making, while also prioritizing implementation in the geographic regions with the highest levels of water risk. The two goals of this project were to develop a methodology to measure and track LinkedIn's embodied water use and impacts from purchased electricity, and to develop a baseline analysis of LinkedIn's embodied water use in purchased electricity and its associated water risks. LinkedIn currently has three different site types: leased data centers, offices, and points of presence, or PoPs. In many cases, the water use associated with purchased electricity primarily comes from sources such as data centers.

1.1 Scope

This project aims to help LinkedIn integrate water positive strategies into its energy procurement and management practices. This project will specifically focus on assessing LinkedIn's Scope 2 water impact of purchased electricity consumed by facilities. Although Scope 2 can also include purchased steam, heating, and cooling, those sources were outside the scope of this project (World Resources Institute, 2015). To achieve this main goal, we conducted literature reviews, explored water metrics, analyzed electricity data from LinkedIn owned and leased facilities, and identified geographic regions with high embodied water withdrawal, consumption, and risk.

This project does not cover direct (Scope 1) water use at LinkedIn facilities or (Scope 3) supply chain water impacts, but may reference them for context. The location-based accounting methodology is utilized in this study, as opposed to the market-based methodology. This approach accounts for the water footprint from the grid electricity use for each of the regions, depending on the characteristics of the grid within the respective region, rather than LinkedIn's renewable energy procurement strategies. So despite the fact that according to LinkedIn from 2022 they use 100 percent of its energy consumption made up of renewable energy from onsite solar power production, green tariffs, and power purchase agreements, this procurement is out of the scope of our project (LinkedIn, n.d.). This research uses a location-based accounting method and does not include market-based accounting. So, all of the findings show the average grid mix of the areas where the facilities are, rather than the effects of purchasing renewable energy.

Our project utilized LinkedIn's electricity consumption as a main source for our findings. Along with that, we did an extensive search looking for multiple water metrics, including water consumption, water withdrawal, and water stress. This scope was primarily focused on these three metrics even though there are other water impact categories that could be looked at in this sense. Our scope also looks at US eGRID regions specifically, as that is the one that LinkedIn primarily utilizes. LinkedIn has operations around the world, but this project will be primarily

focused on the United States only, since that is where over 97% of electricity consumption occurs.

1.2 Literature Review

1.2.1 Water accounting and report

With the rise of AI, the demand for data centers is increasing, leading to a significant increase in water consumption. Data center water needs are projected to grow from about 60 billion liters in 2022 to 150-275 billion liters by 2028 (Satariano, A et al.,2026). Sustainability is a big deal for businesses all over the world, and this is an important part of ESG reports. In these reports, greenhouse gas emissions assessments are often considered core indicators because they provide a standardized method for quantifying corporate carbon emissions. However, compared to the mature development of carbon emissions assessment systems, the methodology for corporate water accounting remains relatively inconsistent. Most companies primarily disclose direct operational water use, but indirect water footprints related to energy use and the supply chain are often not fully quantified. Therefore, developing methods to assess the impact of indirect water use by companies, particularly the water impact related to data center electricity consumption, is becoming increasingly important.

To define the boundary of this study, we use scope 2 GHG emissions as a baseline for our main focus; scope 2 water use. Under GHG emissions, there are scopes 1, 2, and 3. Scope 1 is direct emissions that include company facilities and vehicles. Scope 2 is indirect emissions for purchased electricity. Scope 3 includes supply chain and other indirect emissions, such as business travel, employee commuting, and end of life treatment of sold products. In this study, we use this framework to analyze the water impact for scope 2 purchased electricity. Although Scope 2 can also include purchased steam, heating, and cooling, these sources are outside the scope of this analysis (Paterson et al., 2015).

Water footprint (WF), on the other hand, is the total volume of freshwater used to produce goods and services consumed by individuals, regions, or countries, which links human consumption to water use and environmental impact (da Silva et al., 2016). The WF, therefore, is not just direct water use, but also indirect water use, often termed 'virtual' or 'implicit' water, which is the water resources consumed in other regions in producing the goods and making them flow to the consumption site through trade. In this sense, in a globalized world, the use of water has become interconnected across regions, and therefore, in the context of supply chains, indirect water use has become an important aspect in the evaluation of the impact of water use. In this respect, the WF is generally said to comprise three types brought out by professor Arjen Y. Hoekstra, creator of the water footprint concept (Water Footprint Network, 2023). The three are blue water, which is the consumptive use of blue water resources, like surface and groundwater; green water, which is the”water in the soil, provided by rainfall, used in plant evapotranspiration”; and grey water, which is the volume of water needed to “dilute pollutants and meet quality standards”(Water Footprint Network, 2023). At the city and enterprise level, due to the high dependency on external supply chains, indirect water use is likely to dominate the total water footprint, implying that direct water use is not a complete reflection of the actual water impact. Based on this understanding, water footprint analysis has gradually expanded beyond conventional agricultural

water use to include the energy sector, including indirect water use from power plants and data centers, emphasizing the need to analyze water footprints from a supply chain perspective.

One of the main causes of indirect water use is the production of electricity. Large amounts of water are used by thermoelectric power plants for steam production and cooling. Based on prior research, water use in power production involves both direct water use at the plant level and indirect water use across the whole life cycle of electricity generation, and electricity generation is a major global cause of water stress (Jin et al., 2019). Research also shows that water consumption and withdrawal vary greatly based on cooling technique. While recirculating cooling systems extract less water but consume more through evaporation, once-through cooling systems remove huge amounts of water but return most of it to the source. For this reason, while evaluating water impacts, water removal and water consumption should be dealt with independently (Jin et al.,2019).

1.2.2 Water Scarcity Method

Guidelines for calculating the water footprint of purchased electric power have been developed by the World Resources Institute, which highlights the importance of connecting data on electrical consumption with regional water intensity standards (World Resources Institute, 2023a). In water resource systems, water consumption means that the amount of water that does not return back to the sources and water withdrawal means that the total amount of water taken from the source (Jin et al., 2019). Water risk assessment tools are crucial for a more comprehensive understanding of water resource management. These tools encompass various factors, such as watershed conditions, operational risk exposure, risk persistence, and vulnerability. Aqueduct is a water risk assessment tool developed by the World Resources Institute. It uses indicators like baseline water stress, drought risk, flood risk, seasonal variability, and water quality to calculate out the risk of water in a particular basin (Kuzma et al., 2023). These indicators help find areas where using water might make operations or the environment riskier. Therefore, Aqueduct can help you understand the bigger picture of LinkedIn's electricity use in terms of water danger.

AWARE is another water risk method different from Aqueduct. AWARE model shows that in a certain area using one unit of water how much stress will be put on the area. To be more specific, if an area is already stressed for water, using little amounts of water will cause a big effect. On the other hand, if the other area uses the same amount of water but the area is not stressed about water then the effect will be little. In this way, AWARE models provide characterization factors for different regions. AWARE applies LCA by weighting water use based on local water scarcity, so the same amount of water can have different impacts depending on location (WULCA, n.d.).

PART II: Methodology

To estimate LinkedIn's Scope 2 water consumption and impacts, we developed a framework that converts electricity consumption into measurable water outcomes. The framework answers three core questions: Where does the electricity LinkedIn purchase comes from, and how water-intensive is that grid?, what is the local water availability in those grids?, and how does LinkedIn's water footprint compare against global water scarcity? Each question requires a different methodological tool, and the three analyses together build a comprehensive picture of LinkedIn's embedded water impact.

The first question: How much water does LinkedIn's facilities electricity consumption require from the grid? is answered by using the Water Impact Tool (WIT), developed by Lawrence Berkeley National Laboratory. The WIT tool assigns water consumption and withdrawal intensity factors (in liters per kilowatt-hour) to each facility based on its Balancing Authority.

The second question: How stressed are the watersheds where that water is actually being drawn from? is addressed by using Aqueduct version 4.0, developed by the World Institute Resources Institute. Aqueduct provides basin-level water stress scores that allow us to assess whether LinkedIn's water use is occurring in regions where water is scarce.

The third question: How does LinkedIn's footprint translate into a globally comparable impact score? is responded by AWARE 2.0 (Available Water Remaining), developed by the WULCA group. AWARE assigns characterization factors that adjust water use based on how scarce water is in a determined location compared to the global average, resulting in standardized impact scores that can be compared across regions.

These tools are used at different scales and answer different questions, and we determined that the use of these different tools could bring valuable insights to this project.

2.1 LinkedIn Data Set

We analyzed LinkedIn's electricity data for the fiscal year spanning July 1, 2023, to June 30, 2024. The data covers all owned and leased facilities under LinkedIn's operational control and includes specific location details such as the address, city, and eGRID region.

While the scope encompasses three property types: Offices, Points of Presence (PoPs), and Data Centers, this last category alone accounts for 95.72% of total electricity consumption. Other facilities like warehouses and parking garages, are excluded from this specific dataset. Finally, the energy totals are provided in MWh and have been verified through third-party assurance for accuracy.

2.2 Tools For Data Analysis

2.2.1 Water IMPACT Tool

The Water Impact Tool, short for Water Integrated Mapping of Power and Carbon Tracker, is a publicly accessible, web-based analytics platform developed by Lawrence Berkeley National Laboratory (LBNL) and funded by the U.S. Department of Energy (Siddik et al., 2024). Its core purpose is to translate electricity consumption into quantified water and carbon impacts, providing intensity factors needed to assess the environmental footprint of electricity use at a highly granular spatial and temporal scale.

The tool was developed to address a critical gap in existing environmental accounting methods. Prior approaches to estimating the water consequences of electricity use are typically generalized across large geographic regions, overlooking the spatial and temporal variability in the electricity mix –including fluctuations in renewable energy availability– that determine the actual environmental impact at any given moment (Siddik et al., 2024). The Water IMPACT Tool addresses this gap by providing hourly estimates of water use for each of the U.S. electricity grid's Balancing Authorities (BAs), making it possible to link a specific facility's electricity consumption to its local grid.

Understanding why BA-level analysis matters requires understanding how the electricity grid actually delivers power to end users. A Balancing Authority is the entity responsible for real-time matching of electricity supply and demand (EIA, 2016). Electricity consumers within a given BA are not using power from a single source: they are consuming a mix of electricity generated by every power plant operating within and interconnected with that authority's territory. Because different generation technologies carry dramatically different water intensities. For example, coal-fired plants average roughly 19,185 gallons of water withdrawn per megawatt-hour, while natural gas combined-cycle plants average approximately 2,803 gallons per megawatt-hour), the water footprint of a kilowatt-hour of electricity varies substantially depending on which fuels dominate the local grid at any point in time (EIA, 2022). The Water IMPACT Tool captures this variation directly, making it the most granular representation of electricity's environmental footprint feasible without requiring assumptions about distribution within a BA (Siddik et al., 2024).

How the Water Impact Tool works: The Core Data Inputs

The Water Impact Tool operates by integrating publicly available data on electricity generation and water use at the power plant level with detailed data between balancing authorities, allowing it to estimate the environmental impact of each unit of electricity supplied to end users in a given BA (Lawrence Berkeley National Laboratory [LBNL], n.d.). Users can interact with the tool by entering a facility address or clicking on the interactive map, which retrieves the corresponding water consumption, withdrawal and CO2-eq emission intensity factors for that location. The tool’s underlying data are also available for download as an Excel file for a given year, and hourly data (LBNL, n.d.).

Intensity Factors

For every BA region, the Water Impact Tool provides two critical hydrological coefficients. The Water Consumption Intensity Factor (L/kWh) measures the volume of water permanently lost from the local watershed per unit of electricity consumed. The Water Withdrawal Intensity Factor (L/kWh) measures the volume of water removed from a source per unit of electricity, including the water that is returned after its use (LBNL, n.d.). We used both metrics to account for the primary allocation of water use for LinkedIn facilities.

Temporal Profiles and Hourly Resolution

A key feature of the Water Impact Tool is its hourly temporal resolution. The electricity grid is continuously evolving, with the share of the generation from coal, natural gas, nuclear, hydro, solar, wind and other sources shifting throughout every hour of every day in response to demand patterns, weather conditions, and grid management decisions (Siddik et al., 2024). Because the water intensity of electricity changes as the fuel mix changes, a single annual average factor cannot accurately represent the footprint of electricity consumed at different times of day. The WIT resolves this by providing distinct intensity factors for daytime and nighttime electricity use, as well as a continuous 24/7 profile. This approach captures a more accurate picture of how water is consumed and withdrawn based on the actual operational cycle of the grid (LBNL, n.d.).

Balancing Authority Mapping

To assign the appropriate intensity factors to a facility, the WIT maps its address or postal code to the corresponding Balancing Authority. This spatial approach is more accurate than state-level data because BA boundaries reflect the actual operational structure of the electricity grid and do not conform to political boundaries (EIA, 2016). The United States is organized into approximately 66 BAs across three major regions: Eastern, Western, and the Electric Reliability Council of Texas (ERCOT), each managing a distinct portfolio of generation resources.

Data Sources

The WIT uses data from several public datasets to construct its BA-level intensity factors. Monthly electricity generation details and fuel types for U.S. power plants come from the EIA Form 923. Water withdrawal and consumption data for larger power plants (over 100 MW) come from the EIA's thermoelectric cooling dataset. Hourly electricity operating data are sourced from the EIA 930 Grid Monitor (LBNL, n.d.).

Geographic and Temporal Scope

The Water Impact Tool covers all U.S. Balancing Authorities within the contiguous (Lower 48) states and provides data spanning 2018 through 2022, with ongoing near-real-time updates hosted at the tool's web interface (Siddik et al., 2024). Alaska, Hawaii, and Canadian and or Mexican BA are not included, though cross-border electricity interchange with Canada and Mexico is captured where it flows to the U.S. systems (U.S. Energy Information Administration [EIA], 2024). The WIT incorporates dynamic data from the EIA 930 Grid Monitor, allowing it to reflect current grid conditions, such as the continued growth of solar and wind generation over time.

Map System: HydroSHEDS

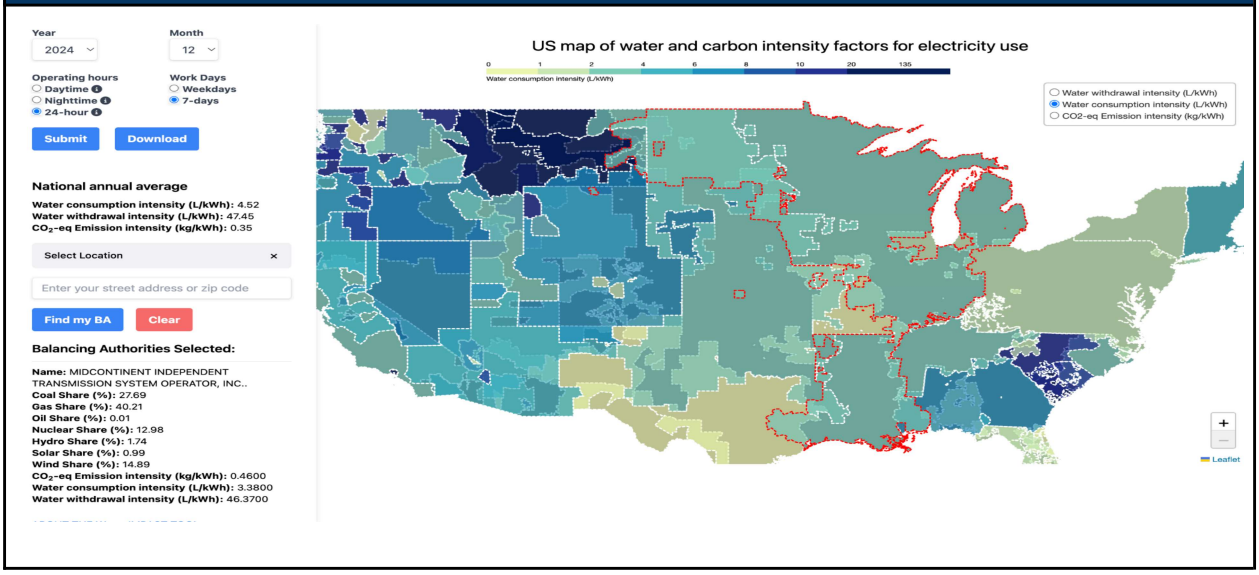
The Water Impact Tool integrates spatial hydrological data from the HydroSHEDS database, developed through a partnership between the World Wildlife Fund and the U.S. Geological

Survey. HydroSHEDS provides globally consistent hydrographic information –including catchment boundaries, river networks, lake shorelines, and drainage directions– derived from the Shuttle Radar Topography Mission digital elevation model at multiple spatial resolutions (HydroSHEDS, 2022). Its suite of secondary products, including HydroBASINS, Hydrorivers, HydroLAKES, and HydroLAKES, and HydroATLAS, support watershed analyses, hydrological modeling, and freshwater conservation planning.

Calculation Method used for LinkedIn Analysis

To determine LinkedIn's specific water impact, we applied the following process. First, each LinkedIn facility's postal code was mapped to its Balancing Authority using the Water IMPACT Tool's interactive map interface, which retrieved the specific liter per kilowatt-hour (L/kWh) water consumption and withdrawal intensity factors –as shown in Figure 1.

Figure 1. Screenshot of Water IMPACT map: Example of retrieving water consumption intensity factors for electricity use in liters per kilowatt-hour.



Note. Adapted From Water IMPACT map by *Lawrence Berkeley National Laboratory.* https://waterimpacttool.lbl.gov

Second, these factors were multiplied by the total kilowatt-hours of electricity consumed by each LinkedIn facility to quantify both consumption and withdrawal volumes. Third, daytime and nighttime energy loads were treated separately, using their respective factors to capture information of how water is consumed versus withdrawn based on the grid's operational cycle across different hours of the day. Finally, to estimate total water use for continuous operations, a 24/7 profile was applied, reflecting typical data center facility operations. This methodology produced a more accurate picture of the actual hydrological footprint of LinkedIn's energy use than a single average annual factor would allow. It can be expressed in the following formula:

$$V = I \times E$$

Where:

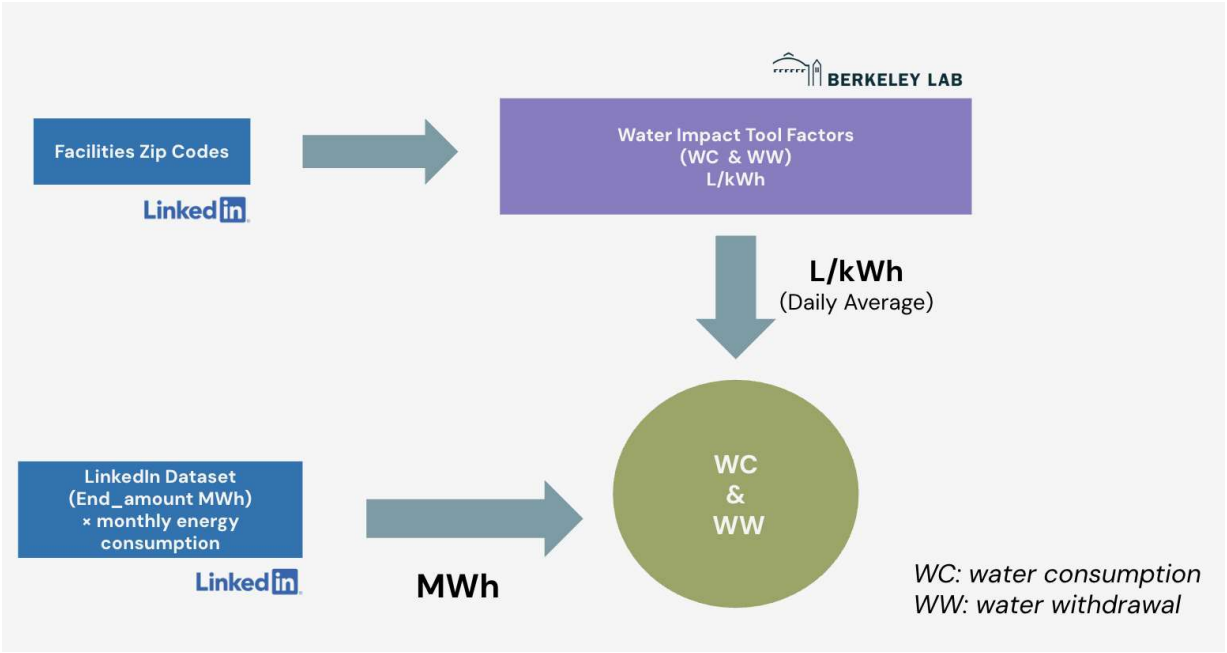
V = water volume (either consumption or withdrawal)

I = water intensity factor (L/kWh)

E = total electricity consumed by LinkedIn facilities (kWh)

Figure 2 illustrates the workflow of our analysis, starting from the upper left. Circles represent the outputs generated, arrows indicate the units provided, and squares the data sources.

Figure 2. Workflow of the calculation method using the Water Impact Tool for LinkedIn water footprint analysis.



Limitations

A primary limitation of the Water Impact Tool –stated on their website– is its reliance on the HydroSHEDS (2022) dataset, which is derived from remote sensing and hydrographic modeling rather than ground-truth measurements. Because these figures are estimated rather than directly observed, the tool's outputs may lack precision in regions with complex hydrology or limited satellite coverage (HydroSHEDS, 2022). Where satellite data are sparse or terrain is highly irregular, the HydroSHEDS-based spatial assessments will be correspondingly less reliable.

A second significant limitation is associated with the spatial data underlying Balancing Authority boundaries. No publicly available GIS dataset of BA polygon regions was found. This absence reduced our ability to directly link BA territories to other spatial units of analysis.

2.2.2 Aqueduct 4.0

Aqueduct 4.0 is the World Resources Institute's (WRI) current global water risk mapping framework. Described by the WRI as the most robust iteration of the platform to date, it translates complex hydrological model outputs into intuitive, decision-relevant indicators of water-related risk for businesses, governments, NGOs, and researchers around the world (World Resources Institute [WRI], 2023a). While the Water Impact Tool operates at the level of the electricity grid to quantify the water footprint of a facility's energy consumption, Aqueduct operates at the level of the watershed to assess whether the water resources available at a given location are under competitive stress. Together, the two tools address complementary dimensions of corporate water risk: One measuring how much water a facility's electricity use costs to the local environment, and the other one measuring if the local environment can sustain that cost.

The indicator we used to develop this project is the Baseline Water Stress (BWS), because it aligned with our goals. In WRI's framework, water stress does not simply mean a lack of water; it measures the ratio of demand to supply by evaluating how much of the naturally available water is being extracted by human activities across all sectors (Kuzma et al., 2023). For example, a river basin where withdrawals are low relative to supply registers a low stress score; on the other side, a basin where agriculture, industry, and municipalities together rely heavily on a limited renewable supply registers high or extremely high stress.

Besides Baseline Water Stress, Aqueduct evaluates a composite of 13 different water risk indicators across three categories: physical quantity risk (including drought, flood, interannual variability, and groundwater table decline), physical quality risks (including untreated wastewater discharge and coastal eutrophication from nutrient runoff), and regulatory and reputational risks (including the percentage of the population lacking access to safe drinking water and sanitation, as well as Environmental, Social and Governance indices) (Kuzma et al., 2023). Each of these indicators can be analyzed individually or combined into composite indices of compound water stress.

How Aqueduct 4.0 works: The Core Data Inputs

Aqueduct integrates data derived from a wide range of publicly available, peer-reviewed sources to construct its 13 indicators. Physical Quantity Data are drawn from PCR-GLOBWB 2 hydrological model (described in detail below). Physical Quality Data are generated from global datasets covering untreated connected wastewater and coastal eutrophication potential from nitrogen and phosphorus runoff. Socioeconomic and Reputational Data comes from the World Health Organization and UNICEF Joint Monitoring Programme for Water Supply, Sanitation and Hygiene, which provides country-level statistics on access to safe drinking water and sanitation, and from RepRisk's Country ESG Risk Index, which tracks governance and environmental liability exposure (Kuzma et al., 2023).

Hydrological Engine: PCR-GLOBWB 2

Aqueduct 4.0 is powered by PCRaster Global Water Balance version 2 (PCR-GLOBWB 2). Developed by the Utrecht University, this is one of the world's most advanced global hydrological models. PCR-GLOBWB 2 places a grid over the entire planet at a resolution of 5 arc-minutes –roughly 10 kilometers by 10 kilometers at the equator. The model runs complex equations to simulate the water cycle for each pixel on a daily basis to estimate rainfall,

evaporation, soil absorption, and groundwater recharge (Kuzma et al., 2023). It integrates demand, withdrawal, and return flows for all major water-use sectors –industrial, domestic, agricultural, and livestock.

This model provides raw data for Baseline Water Stress estimates, providing Aqueduct with exactly how many cubic meters of water are naturally available in a specific grid, versus how many cubic meters are being withdrawn for human purposes.

Map System: HydroBASINS level 6

While PCR-GLOBWB 2 produces raw water balance estimates at a 5 arc-minute pixel resolution, Aqueduct does not report risk at this scale –individual 10 km pixels are too spatially granular and statistically noisy for strategic corporate decision-making. Instead, the tool aggregates PCR-GLOBWB 2 outputs into the HydroBASINS Level 6 sub-basin framework (Kuzma et al., 2023). HydroBASINS is a global database of vectorized polygon maps developed by the World Wildlife Fund as part of the HydroSHEDS project –the same foundational hydrographic dataset used in the Water Impact Tool's spatial architecture. It solves a fundamental challenge in applied hydrology: nature does not draw straight lines or consistent borders.

HydroBASINS subdivides the world's landmass into a hierarchical set of standardized drainage basins. Level 1 represents the continental scale, and each successive level divides these into progressively smaller sub-basins. Level 6 produces approximately 16,400 sub-basins globally, with a median area of about 5,318 square kilometers –roughly the size of the U.S state of Delaware (Kuzma et al., 2023). WRI determined that this scale represents an optimal balance for corporate water risk analysis: small enough for regional insights yet large enough for global standardization.

Geographic and Temporal Scope

Aqueduct provides both historical baselines and future climate projections. The baseline period spans 1979 to 2019, offering over 40 years of hydrological data for the four core quantity-based indicators –stress, depletion, seasonal variability , and interannual variability (WRIM 2023b). For future projections, it extends to milestone years of 2030, 2050, and 2080.

Risk Scoring and the Baseline Water Stress Formula

Aqueduct normalizes all raw hydrological and socioeconomic data into a standardized risk score ranging from 0 to 5, where 0 represents low risk and 5 represents extremely high risk. For Baseline Water Stress specifically, the raw value (bws_raw) represents the physical ratio of total annual withdrawals to available renewable water supplies, while the equivalent score (bws_score) maps this ratio onto the 0 to 5 scale. Mathematically, Baseline Water Stress is defined as:

$$BWS = Total\ Annual\ Water\ Withdrawals\ /\ Mean\ Available\ Blue\ Water$$

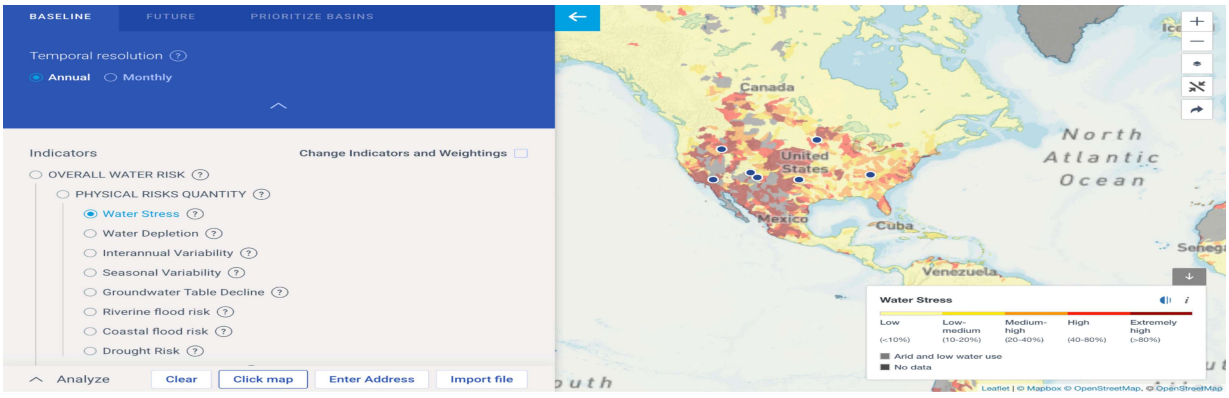
Where Total Annual Water Withdrawals represents total annual gross demand –including industrial, domestic, agricultural, and livestock withdrawals– and the Mean Available Blue Water represents total available renewable surface and groundwater, specifically adjusted to account for water already consumed by upstream users (Kuzma et al., 2023).

Under this framework, basins with less than 10% of renewable supplies withdrawn score in the low range (0–1); low-medium (1–2) levels indicate minimal competition; the medium–high range (2–3) serves as a warning zone; and the high (3–4) and extremely high (4–5) categories –representing withdrawals ratios above 40% and 80% respectively– indicate regions where the intensity of competition over shared water sources significantly elevates the risk of supply disruptions for all users (Kuzma et al. 2023).

Calculation Method used for LinkedIn Analysis

Spatial Join - Linking facility Locations to Watershed Water Stress: To assign a Baseline Water Stress value to each LinkedIn facility, a spatial join was performed between the facility location dataset provided by LinkedIn and the Aqueduct 4.0 shapefile –a non-topological geospatial vector data format used in GIS software–. The Aqueduct shapefile is a global polygon in which each polygon represents a HydroBASINS Level 6 sub-basin and carries the full suite of Aqueduct water risk attributes as tabular fields. By overlaying the point geometry of each facility (defined by its latitude and longitude) against this polygon layer, each facility was assigned the bws_raw and bws_score values of the sub-basin within which it falls. Figure 3 illustrates this spatial join:

Figure 3. *Screenshot of Aqueduct Water Risk Atlas: Example of spatial join of a facility location (points) to Aqueduct Water Risk Atlas map, using the water stress indicator (bws_raw and bws_score).*



Note. Adapted from *Aqueduct Water Risk Atlas*, by World Resources Institute (n.d.) https://www.wri.org/applications/aqueduct/water-risk-atlas/

Aggregation to eGRID regions: Once each facility was assigned a local bws_raw value through the spatial join, the analysis required the aggregation facility's level water stress up to the scale of the EPA's Emissions and Generation Resource Integrated Database (eGRID) regions. This scale was necessary because the Water Impact Tool uses Balancing Authorities (BAs) and their corresponding eGRID regions to estimate the water intensity of electricity consumed at each facility. Matching Aqueduct data to the same eGRID geography is a consistent spatial framework that allows water stress in the generation mix to be interpreted alongside the consumption already captured by the Water Impact Tool.

Weighted Stress Index Calculation: To quantify how much water-stressed generation underlies each facility's electricity supply, a Weighted Stress Index (WSI) was done at the eGRID region level. For each region, every power–generating facility within the region was first assigned a bws_raw value. A generation-weighted stress score was then computed by multiplying each facility's annual net generation output by its bws_raw, summing these products across all assets in the region, and dividing by the region's total annual net generation. Formally:

$$WSI_r = (\Sigma_i E_i \cdot BWS_raw_i) / \Sigma_i E_i$$

Where the summation runs over all generating assets i within eGRID region r, and:

WSI_r = Weighted Stress Index for eGRID region r

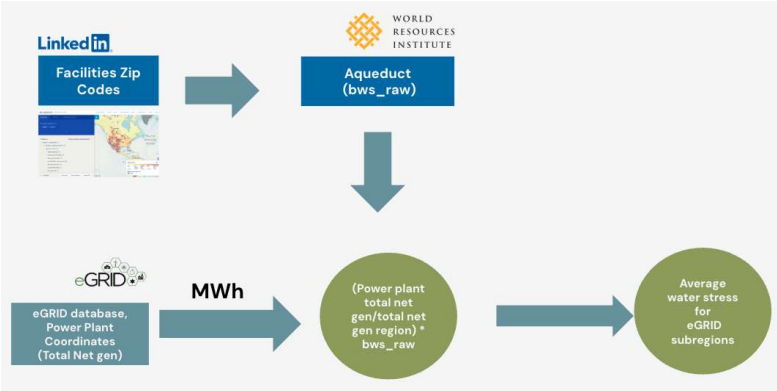
E_i = Annual net electricity generation of asset i (MWh)

BWS_raw_i = Baseline Water Stress raw ratio of asset i, obtained via spatial join to the Aqueduct 4.0 shapefile.

The resulting WSI_r represents the generation-weighted average water stress of the electricity mix in each region. A region with a high WSI_r generates much of its electricity from plants located in watersheds where human withdrawals are already a large fraction of available renewable supply, meaning the indirect water risk embedded in that facility's electricity consumption is high, even before the facility's direct water use is considered. This metric was used to rank eGRID regions by embedded water stress and to identify which LinkedIn facilities are served by the most water-stressed generation mixes.

Facilities with a bws_raw of 40% or greater were classified as operating in water-stressed watersheds directly. The distribution of facilities across risk tiers was then visualized as pie charts, allowing a summary view of the share of the LinkedIn portfolio exposed to high-stress conditions at both the facility level and the eGRID region level. Figure 4 illustrates the workflow of this calculation.

Figure 4. *Workflow of the calculation method for LinkedIn water footprint analysis using Aqueduct.*



Limitations
A central limitation of Aqueduct 4.0 is that it is explicitly designed as a prioritization and screening tool rather than a precise measurement instrument. WRI acknowledges that key elements of the composite risk framework cannot be directly validated against observed outcomes, since they aggregate indicators across income measurable dimensions of water risk (WRI, 2023a).

A second limitation is that the PCR-GLOBWB 2 model operates at a spatial resolution that may fail to capture localized hydrology. Sub-basins at HydroBASINS Level 6 average roughly 5,318 square kilometers, meaning that highly localized water stress or scarcity events –such as those driven by specific aquifer depletion or a single large industrial withdrawal– can be averaged out and underrepresented in the risk score (Kuzma et al., 2023).

2.2.3 AWARE 2.0

AWARE 2.0 (Available Water Remaining version 2.0), is a consensus-based water scarcity impact assessment method developed by the WULCA working group under mandate from the UNEP-SETAC Life Cycle Initiative (WULCA, n.d.–a). It is specifically designed for use as a midpoint Life Cycle Impact Assessment (LCIA) indicator in Life Cycle Assessment (LCA), where the central question is: what is the potential for a unit of freshwater consumed in a given watershed to deprive another user –human or ecosystem– of that water (WULCA, n.d.–b)? By situating AWARE 2.0 within the LCA framework, the tool goes beyond simply accounting for how much water a facility or product system uses and instead characterizes the environmental relevance of that consumption relative to local water availability.

While the Water Impact Tool quantifies the water volume associated with each kilowatt-hour of electricity consumed and Aqueduct assesses the competitive pressure on local watershed resources from all human withdrawals, AWARE 2.0 provides a third complementary layer of analysis. It translates each cubic meter of water consumed by a facility's electricity supply into an impact score expressed in world-equivalent cubic meters (m^3 world eq), reflecting how much more or less scarce water is at that specific location compared to the global average. Additionally, AWARE 2.0 operates strictly within the domain of physical water quantity. It does not address water quality, governance, regulatory risk, or future climate projections.

AWARE 2.0 was published in 2025 (WULCA, n.d.–c) and improves on the original AWARE consensus method by use more recent input data, and fully consistent hydrological model outputs for WaterGAP 2.2e improved representation of environmental water requirements, and explicit handling of special hydrological features such as river deltas and inland sinks (WULCA, n.d.–c).

AWARE 2.0 characterization factors (CFs) measure the potential to deprive another freshwater user by consuming water in a region where remaining water availability per unit area is already low.

How AWARE 2.0 works: The Core Data Inputs
The calculation of AWARE 2.0 characterization factors requires three categories of input data, all derived from the WaterGAP 2.2e global hydrological model. The first is *natural water availability*, estimated from surface runoff and groundwater recharge data generated by

WaterGAP's Global Hydrology Model component, which simulates rainfall, snowmelt, evapotranspiration, soil infiltration, and river discharge for each grid cell. The second is *human water demand*: empirical estimates of consumptive water use by agriculture (irrigation), manufacturing industry, domestic households, thermal power plant cooling, and livestock. The third is the *Environmental Water Requirement (EWR)*, which reserves the minimum ecological flow that must remain in rivers and lakes to preserve aquatic biodiversity. This ecological reservation is a critical feature distinguishing AWARE 2.0 from simpler water stress ratios such as those used in Aqueduct 4.0's Baseline Water Stress indicator, which accounts for human withdrawals but does not explicitly for an ecological focus.

Hydrological Engine: WaterGAP 2.2e

AWARE 2.0 is powered by the WaterGAP (Water Global Assessment and Prognosis), specifically version 2.2e (WULCA, n.d.–d). WaterGAP is one of the world's most established global hydrological models and consists of two components. The Global Hydrology Model simulates the natural water cycle on a standard global grid of 0.5° × 0.5° resolution (roughly 55 km × 55 km at the equator), calculating precipitation, evapotranspiration, surface runoff, and groundwater recharge on a daily time step. The Global Water Use Model simulates consumptive water use across five sectors: domestic, manufacturing, thermal power plant cooling, livestock, and agricultural irrigation.

Map System: Custom-built

AWARE 2.0 uses its own highly specific, custom-built map of 9,406 natural river basins as its primary spatial unit for Life Cycle Inventory impact characterization. These watersheds boundaries are strictly determined by topography, they follow the actual physical flow paths of water rather than the spatial frameworks used by the other tools mentioned before: the Water Impact Tool operates within Balancing Authority boundaries defined by electricity grid topology, and Aqueduct 4.0 aggregates hydrological model outputs to HydroBASINS Level 6 sub-basins. The AWARE 2.0 delineation is optimized for LCA footprinting accuracy rather than for corporate risk communication or electricity accounting.

Spatial and Temporal Scope

AWARE 2.0's Characterization Factors (CFs) are calculated at the sub-watershed level on a monthly time step, based on WaterGAP 2.2e model output spanning the 30-year historical period from 1990 to 2019 (WULCA, n.d.–c). This monthly resolution is essential for two reasons. First, water stress is highly seasonal: many watersheds that appear water-secure on an annual average basis experience significant scarcity during dry-season months when river flows are low and agricultural demand peaks simultaneously. Applying an annual average CF to a facility that consumes electricity year-round would smooth over these temporal extremes and underestimate the impact of summer consumption in seasonally stressed basins. Second, monthly CFs allow LCA practitioners to pair a facility's monthly electricity consumption data with the CFs for the corresponding month and watershed, producing temporally differentiated water scarcity footprint that better reflects when and where the impact actually occurs.

Characterization factors

In LCA, characterization factors (CFs) are the numerical coefficients that translate a unit of water consumed into its actual environmental impact based on local conditions. AWARE 2.0's CFs are

expressed in units of m^3 world eq / m^3 consumed (world-equivalent cubic meters per cubic meter consumed), meaning they represent how many times more or less scarce water is at the assessed location relative to the global consumption-weighted average watershed (WULCA, n.d.–b). A High CF Score indicates a region where water is highly limited. Using water here carries a greater environmental penalty. A Low CF Score indicates a region where water is relatively abundant. The scale is bounded between 0.1 and 100 to avoid extreme values in very arid or very water-rich regions from dominating inventory results.

The AWARE 2.0 impact characterization is built on the concept of Availability Minus Demand (AMD) (Boulay et al., 2018).

Availability Minus Demand = Water Availability – Human Demand – Environmental Water Requirement

where:

Availability Minus Demand (AMD) = Available water remaining in basin
Water Availability = Actually available water after human intervention
Human Demand = Total human water consumption across all sectors
Environmental Water Requirement (EWR) = Environmental Water Requirement

The AMD value is then normalized by watershed area and inverted relative to the global world-average AMD, producing the CF for each basin and month. The CF scale runs from 0.1 (abundant water; low scarcity impact) to 100 (extremely scarce; high impact), with a value of 1 corresponding to the world average AMD per unit area. A CF of 10 means that one cubic meter consumed in that basin is functionally equivalent, in terms of water deprivation potential, to consuming 10 cubic meters at the global average location (WULCA, n.d.–b).

Calculation Method used for LinkedIn Analysis

To estimate the AWARE 2.0 factors for LinkedIn facilities (including offices, points of presence, and data centers), we used annual characterization factors (CFs) for an unspecified water consumption sector (default) at the U.S. eGRID level. The water footprint associated with purchased electricity was calculated by multiplying each facility's water consumption in liters per kilowatt-hour by the corresponding AWARE factors in cubic meters world equivalent. Because these facilities operate year-round, monthly CFs from January through December were applied and paired with water consumption.

However, after completing this approach, we shifted to a spatial analysis using ArcGIS to better capture a full picture. We mapped power plant locations supplying LinkedIn electricity and overlaid them with eGRID regions to better represent the electricity supply mix. From this, we calculated a weighted average water stress factor for each region based on power generation sources, including Fossil Fuel, and Renewable.

This regional average was then multiplied by water consumption and water withdrawal values (in liters) from the Water Impact Tool. This approach better captures the reality that LinkedIn's electricity is sourced from the grid rather than directly from facility locations. By accounting for

the full grid mix and its associated water stress, this method provides a more accurate representation of the water footprint associated with electricity consumption. Figure 5 illustrates the workflow using this tool.

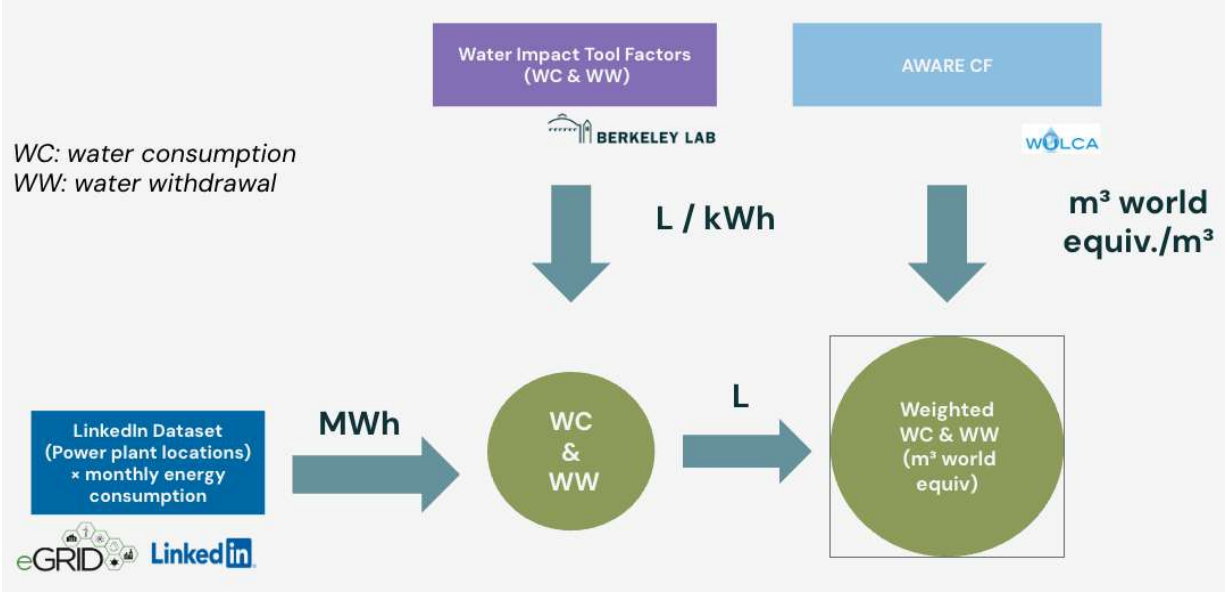
This method is represented by the following formula:

$$WF=(1000/V)\times CF_{avg}$$

Where:

WF = Water Footprint (m^3 world eq.)
V = Water volume from the Water Impact Tool (liters –either consumption or withdrawal)
CF_{avg} = Weighted average characterization factor for the eGRID region (m^3 world eq./m^3)

Figure 5. *Workflow of the calculation method for LinkedIn water footprint analysis using AWARE 2.0.*



Limitations

A set of limitations applies to this tool. First, like Aqueduct's composite risk scores, AWARE's characterization factors simply complex, multidimensional water scarcity dynamics into a single indicator based on availability. In addition, it does not include important local socio–political and infrastructural factors. Second, AWARE relies on global hydrological modeling frameworks that cover large areas rather than specific local conditions. As a result, localized variations in water availability –such as seasonal extremes– may be averaged out, potentially underrepresenting severe water scarcity conditions.

PART IV: Results

4.1 Summary of Results

This study evaluates LinkedIn's electricity-related water impacts using three tools: volumetric water use (WIT), scarcity-weighted impact (AWARE), and baseline water stress (Aqueduct). Together, these approaches provide a comprehensive understanding of how electricity use translates into water-related impacts.

One takeaway is the indirect (electricity-related) water footprint far exceeds the water footprint from direct operations. Electricity-related water withdrawal is roughly 64 times higher than direct withdrawal, and water consumption is about 9 times higher. In practice, this means that most of LinkedIn's water impact is driven by electricity generation rather than onsite operations. Regional patterns also differ depending on how water impact is measured. Under the WIT model, NWPP stands out due to high water consumption, largely linked to hydropower, while ERCT dominates water withdrawal due to thermoelectric cooling. When water scarcity is taken into account through AWARE, the picture shifts slightly: NWPP remains the largest contributor to consumption, but CAMX becomes more prominent, and ERCT remains the main withdrawal hotspot.

The Aqueduct analysis adds a spatial perspective by focusing on water stress. Around 30% of LinkedIn's properties are located in high or extremely high water-stressed areas, representing about 40% of total electricity consumption. At the regional level, CAMX emerges as the most water-stressed region, while ERCT becomes particularly important because it combines high water withdrawal with relatively high stress. NWPP, on the contrary, has the highest water consumption but is evaluated as a lower stress area.

Taken together, these results show that both how much water is used and where it is used matter. For LinkedIn, the most critical regions are those where high electricity demand coincides with high water scarcity. ERCT and SRVC stand out as major water withdrawal hotspots, NWPP as the largest driver of water consumption, and CAMX as the highest water stress risk region. These findings suggest that energy sourcing and operational decisions should be prioritized in high-risk regions such as ERCT and CAMX to effectively manage water impact.

4.2 WIT - Electricity-related Water Volume

The Water Impact Tool (WIT) was used to estimate electricity-related water consumption and withdrawal across LinkedIn's key eGRID regions.

4.2.1 Estimate of LinkedIn's Scope 2 Water Consumption and Water Withdrawal by Facility Type

Among LinkedIn's three property types (data centers, offices, and Points of Presence, or PoPs), data centers overwhelmingly dominate electricity demand. As shown in table 1, LinkedIn's data centers consumed 744,909 MWh of electricity in 2024, accounting for approximately 96% of total electricity use. In comparison, offices and PoPs together contribute only 4% of total consumption.

This concentration of electricity demand in data centers directly translates into a concentration of water impacts. As shown in figure 5 and 6, data centers drive the most electricity-related water impact in both water consumption (95.47% of total) and water withdrawal (96.85% of total). In 2024, as shown in figure 5 and 6, electricity-related water withdrawal (34,753,457 m^3) was approximately 64 times greater than direct withdrawal (542,396 m^3). The electricity-related water consumption (2,981,066 m^3) was approximately 9 times greater than direct consumption (340,627 m^3). This highlights the importance of assessing scope 2 water impact for LinkedIn to make more sustainable operational decisions.

Table 1, LinkedIn Annual Electricity Consumption by Site Type

SiteType	Electricity Consumption (MWh)	Percentage of Electricity Consumption
Data Center	744,909	96%
Office	32,074	4%
PoP	1,252	0%
Total	778,236	100%

Figure 5. LinkedIn Indirect Water Consumption by Site Type

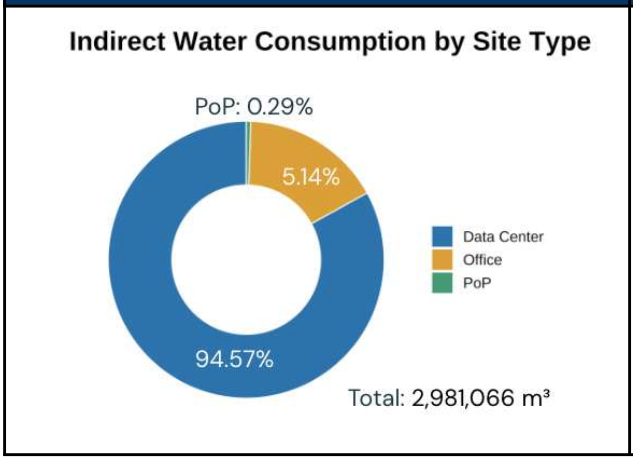
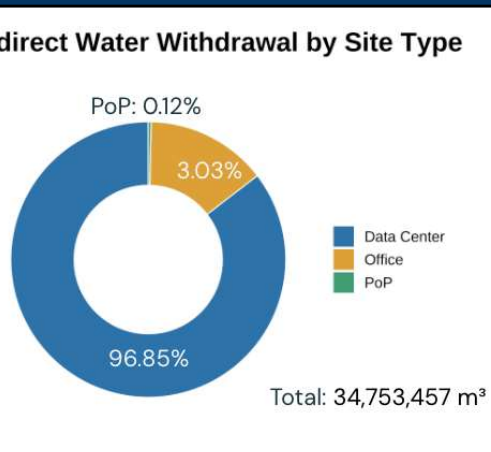


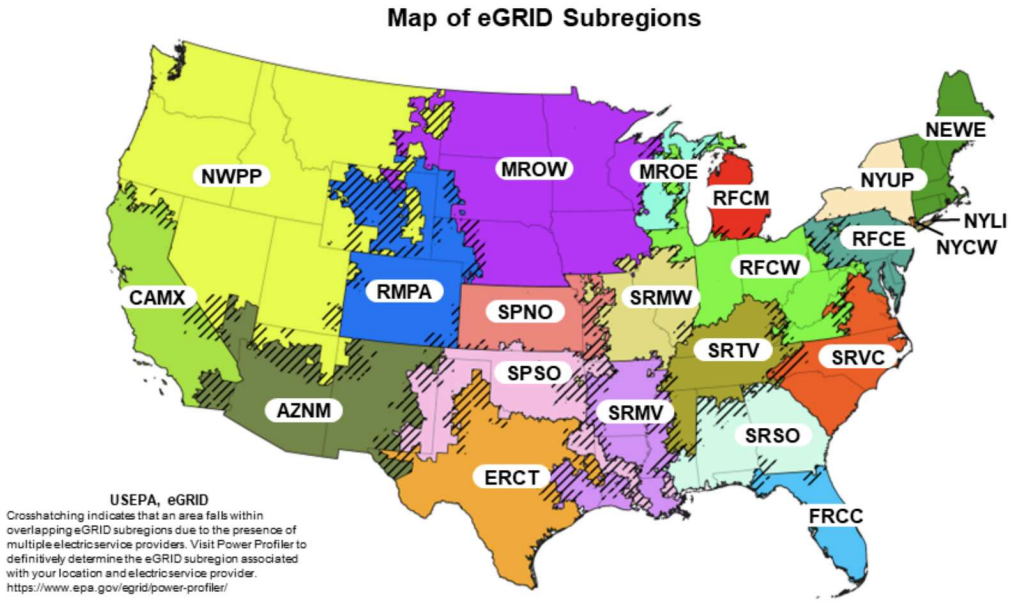
Figure 6. LinkedIn Indirect Water Withdrawal by Site Type



4.2.2 Estimate of Water Consumption and Water Withdrawal by eGRID

We use eGRID regions, as shown in figure 7, to identify the regional result of water impact. While LinkedIn's facilities are located in a total of 10 eGRID regions, its data centers are concentrated in only the four eGRID regions: CAMX, NWPP, ERCT, and SRVC. The four regions are highest in total water impact.

Figure 7, Map of eGRID regions from EPA



At the regional level, water use is not evenly distributed. As shown in Table 2, NWPP has the highest consumption of the eGRID regions (67.14% of total). LinkedIn's assets contributing to this are 2,003,328 m³. However, the region ranks third in water withdrawal, trailing both ERCT (46.45% of total) and SRVC (38.48% of total).

Table 2, WIT Water Consumption and Water Withdrawal in each eGRID region

eGRID Region	LinkedIn Water Consumption m³	LinkedIn Water Withdrawal m³	LinkedIn Electricity Consumption MWh	WC Intensity m³/MWh
NWPP	**2,003,328**	3,978,467	166,213	**12.05**
SRVC	493,848	13,368,469	269,588	1.83
ERCT	291,231	**16,138,875**	**303,320**	0.96
CAMX	169,960	909,666	30,598	5.55
MROW	14,585	152,249	3,821	3.82
NYCW	3,329	96,858	2,530	1.32
RFCW	2,896	77,848	1,586	1.83
RFCM	1,656	24,733	451	3.67
RFCE	225	6,105	123	1.83
FRCC	6	187	4	1.50
Total	2,981,064	34,753,457	778	3831.70

Figures 8 and 9 further illustrate the spatial relationship between electricity consumption and water impacts across regions. These maps show that regions with higher electricity use generally correspond to higher water impacts, particularly in ERCT and SRVC for water withdrawal and NWPP for water consumption.

These regional differences can be partially explained by variations in electricity generation mix. For example, NWPP has a relatively high share of hydropower (38.7%), which is associated with greater water consumption due to evaporative losses from reservoirs. In contrast, ERCT relies heavily on natural gas generation (48.8%) with very limited hydropower (0.1%), and SRVC relies heavily on both natural gas (40.1%) and nuclear power (40.0%). These thermoelectric generation sources require substantial water withdrawal for cooling processes, leading to higher withdrawal volumes in these two regions. CAMX presents a more diverse energy mix profile, including natural gas (41.5%), solar (20.0%), and hydropower (14.1%), resulting in a more balanced water use profile. Detailed fuel mix data for each region can be found in Appendix Table A1.

Figure 8. LinkedIn Water Consumption and Electricity Use by eGRID Region

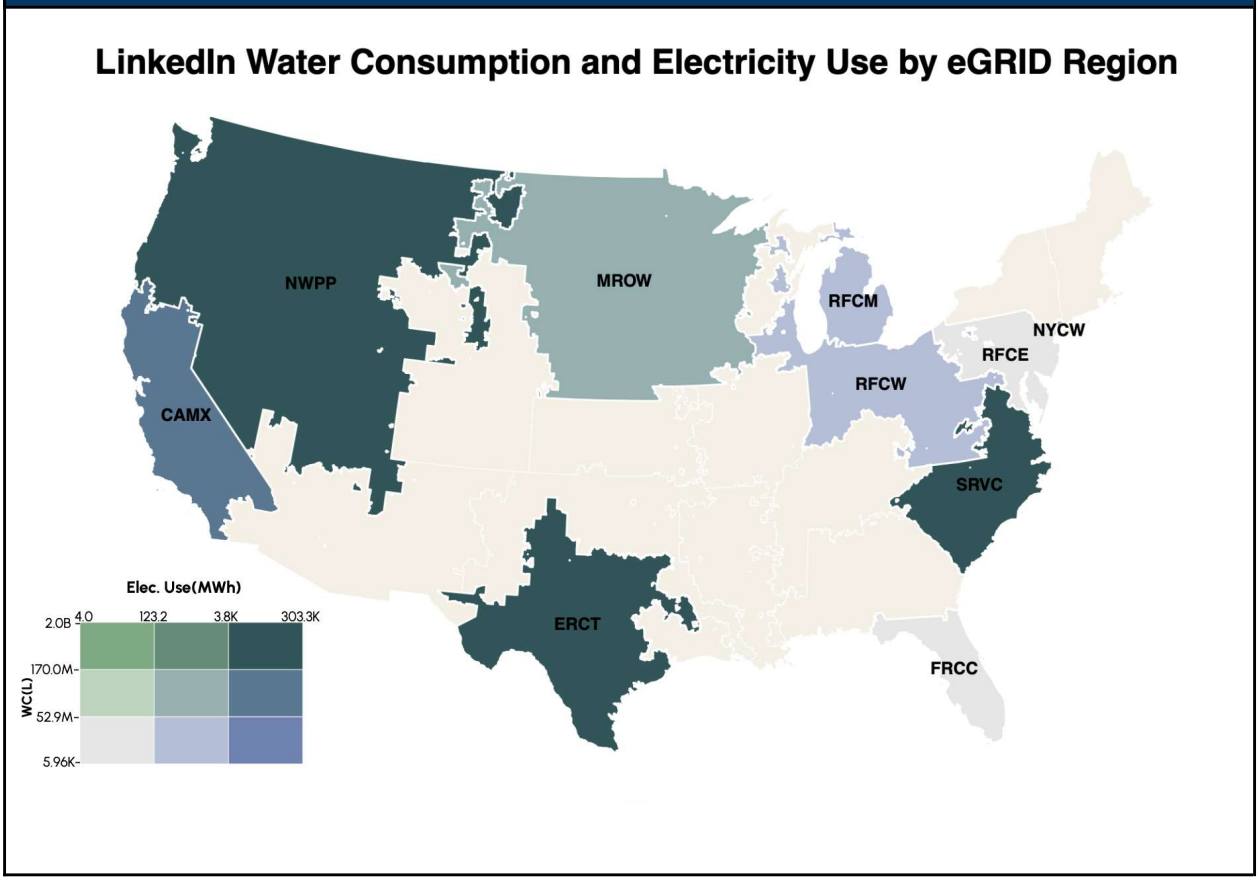
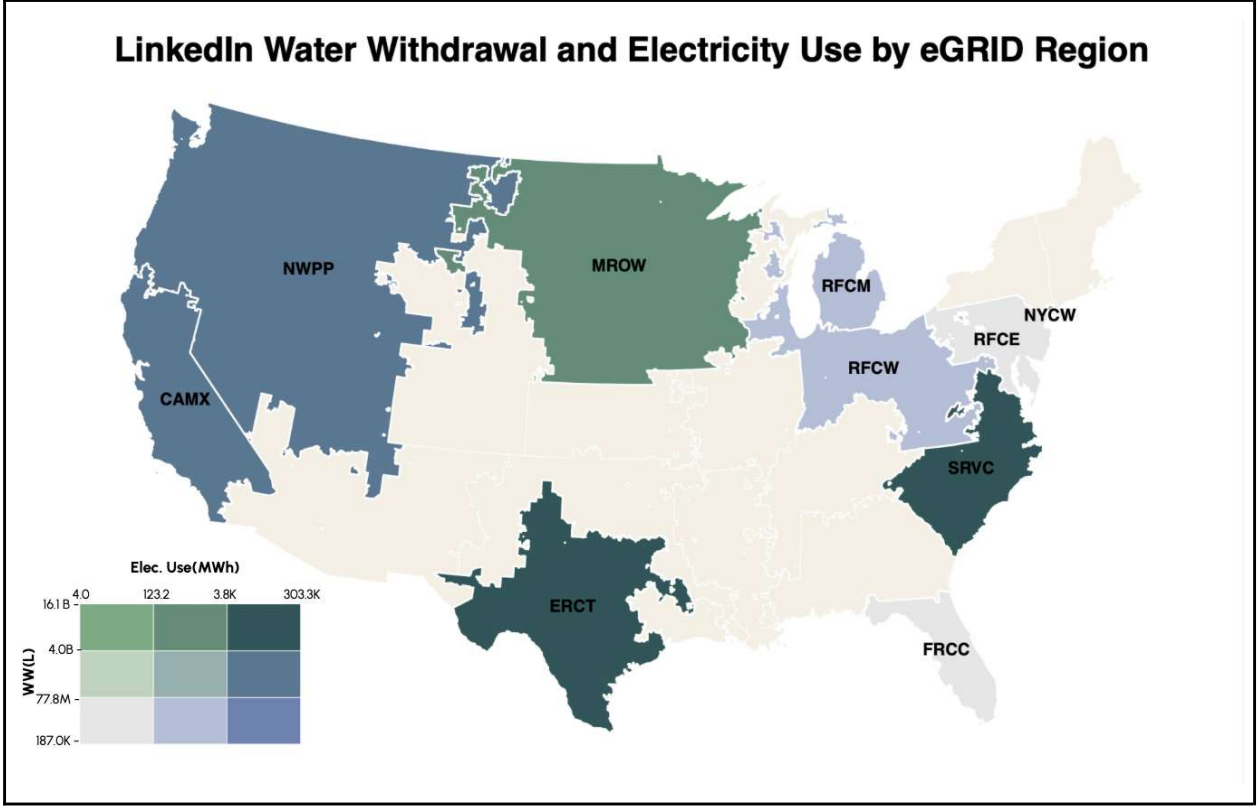


Figure 9. LinkedIn Water Withdrawal and Electricity Use by eGRID Region



These findings highlight the importance of understanding water consumption and withdrawal by evaluating regional electricity generation fuel difference.

Overall, NWPP represents a consumption-intensive region (12.05 m^3/MWh), while ERCT and SRVC represent withdrawal-intensive regions. This distinction has important implications for how LinkedIn prioritizes water management strategies.

While WIT captures the physical volume of water use, it does not account for regional water scarcity. As a result, regions with high water use can not be concluded as those with the greatest environmental impact. To address this limitation, the AWARE model is applied in the next section, incorporating regional scarcity through characterization factor. Adding the scarcity characterization factors (CFs) is important in understanding regional differences in water impact.

4.3 AWARE 2.0 - Weighted Water Consumption and Withdrawal

The AWARE model was applied to assess scarcity-weighted water impacts by incorporating regional characterization factors into water consumption and withdrawal. Compared to the WIT results, AWARE provides a more comprehensive view of environmental impact by accounting for differences in regional water availability. As shown in table 3, among all regions, NWPP remains the largest contributor to weighted water consumption, while ERCT continues to dominate weighted water withdrawal.

Table 3, AWARE Water Consumption and Water Withdrawal in each eGRID region

eGRID region	AWARE Water Consumption m^3 world equiv	AWARE Water Withdrawal m^3 world equiv	Electricity Consumption MWh
NWPP	**38,063,226.18**	75,590,866.83	166,213.40
CAMX	11,217,380.50	60,037,974.14	30,598.25
ERCT	3,203,545.10	**177,527,629.82**	**303,320.34**
SRVC	987,696.95	26,736,938.83	269,588.08
MROW	189,610.11	1,979,240.53	3,820.96
NYCW	3,329.22	96,858.19	2,529.95
RFCW	2,896.39	77,847.77	1,586.02
RFCM	1,656.05	24,732.59	451.37
RFCE	225.20	6,104.52	123.23
FRCC	29.37	934.90	4.03
Total	53,669,595.06	342,079,128.10	778,235.63

As demonstrated in Figure 10, the overall weighted water consumption peaks between April and June. Among four regions, NWPP shows the most obvious seasonal variation in water consumption, despite its relatively stable electricity consumption throughout the year. The increase is more likely driven by changes in water intensity rather than electricity demand. As mentioned in previous analysis, NWPP has a high share of hydropower (38.7%), which is associated with evaporative losses from reservoirs. During spring, there is an increase in the volume of meltwater available and an increase in temperature, which causes an increase in evaporation, leading to higher intensity of water usage (m^3/MWh).

In contrast, water withdrawal shows relatively stable patterns across regions and the year, as shown in figure 11. For example, ERCT, which is dominated by thermoelectric power generation (70.45% of total), exhibits consistently high water withdrawal throughout the year. This is because thermoelectric power plants require continuous water withdrawal for cooling processes, which are less sensitive to seasonal variation. While slight increases may occur during warmer months, this is associated with higher electricity demand.

Therefore, the seasonal variation in weighted water consumption and water withdrawal can be associated with fuel mix and variation in electricity consumption.

Figure 10. Stack Graph of the Weighted Water Consumption by top 3 eGRID Region

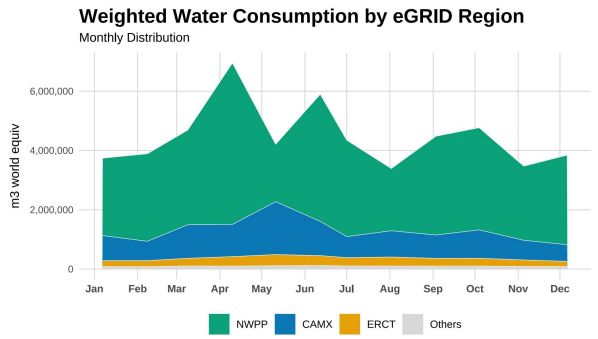
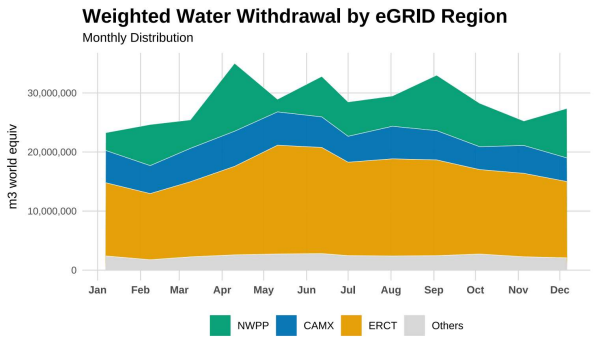


Figure 11. Stack Graph of the Weighted Water Withdrawal by Top 3 eGRID Regions



Compared to WIT, the relative importance of regions changes. Figures 12 and 13 compare the WIT results with the AWARE results for the four key eGRID regions. Because WIT measures physical water volume while AWARE reports scarcity-weighted impact in m^3 world equivalent, the two metrics are not directly comparable in magnitude. However, comparing the regional rankings shows how the relative importance of each region changes once AWARE characterization factors are applied.

For water consumption, NWPP remains the largest contributor under both WIT and AWARE. This indicates that NWPP has both high physical water consumption and a high weighted impact. However, CAMX shows the most significant upward shift. It has the lowest WIT water consumption among the four regions, but becomes the second largest contributor under AWARE. This indicates that water use in CAMX is assigned a higher environmental impact under the AWARE model.

For water withdrawal, ERCT remains the dominant region under both WIT and AWARE, meaning its high physical withdrawal also translates into the highest scarcity–weighted withdrawal impact. NWPP increases in relative importance, moving from third under WIT to second under AWARE. CAMX also increases, moving from the lowest WIT withdrawal region to third under AWARE. In contrast, SRVC drops substantially, from the second–highest WIT withdrawal region to the lowest AWARE withdrawal impact.

Figure 12. Water Consumption by eGRID Region: WIT vs AWARE

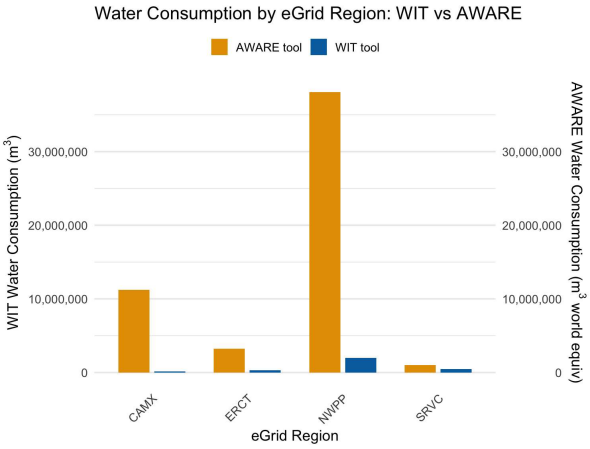
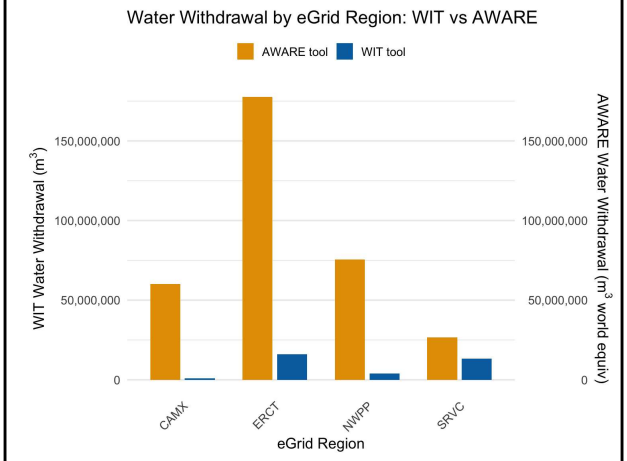


Figure 13. Water Withdrawal by eGRID Region: WIT vs AWARE



Overall, the AWARE results show that regional importance changes once water use is weighted by scarcity factors. NWPP and ERCT remain major contributors, CAMX becomes more important when scarcity factors are considered, and SRVC becomes less important despite its high physical withdrawal under WIT. These results highlight that incorporating water scarcity significantly alters regional priorities compared to volumetric water use alone

While AWARE adds regional scarcity factors to water impact, we utilized Aqueduct in the next section to assess water stress conditions associated with electricity generation across regions. This provides an additional analysis to water volume (WIT) and scarcity-weighted impact (AWARE), by directly examining regional water availability.

4.4 Aqueduct 4.0 - Estimating Regional Water Stress Level

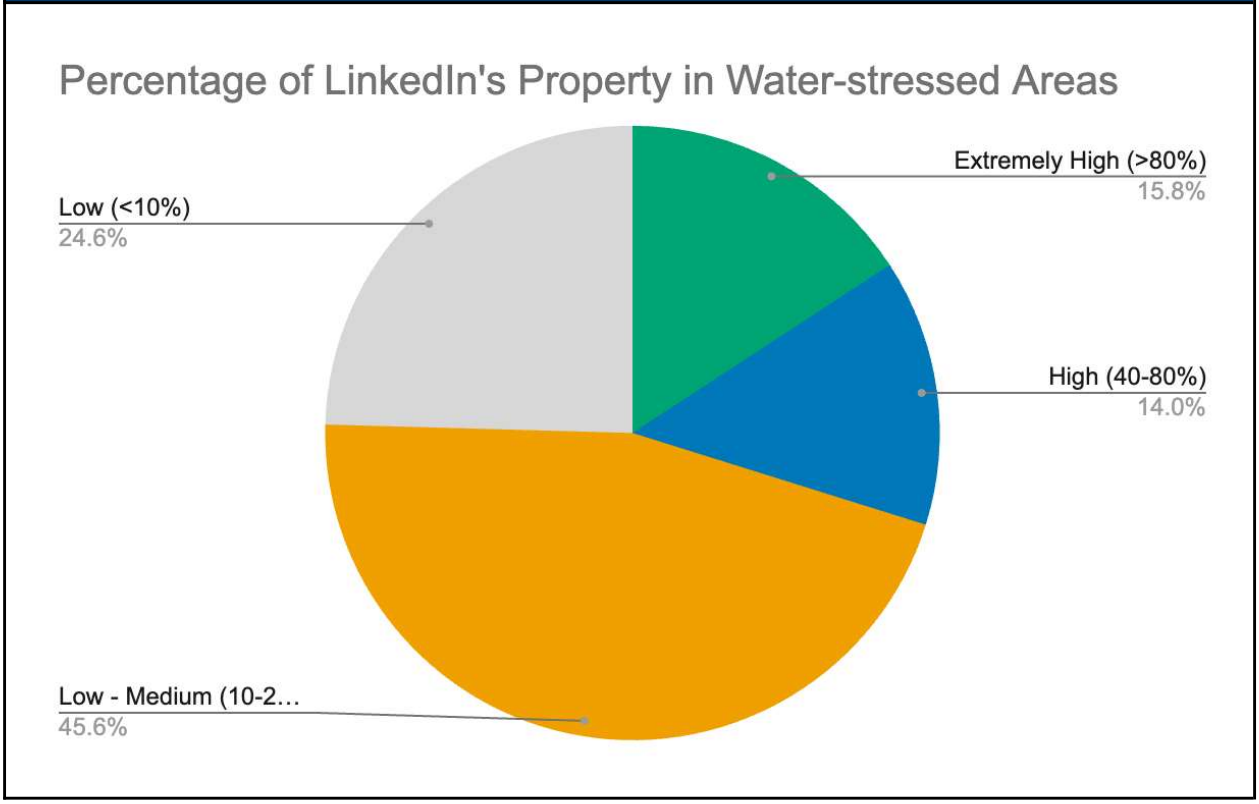
Aqueduct was used to evaluate baseline water stress associated with LinkedIn's facility locations and electricity-related water impacts. Unlike WIT, which estimates the physical volume of water consumption and withdrawal, Aqueduct provides a regional water stress evaluation by identifying where water resources are already under competitive pressure. This section therefore uses Aqueduct to assess whether LinkedIn's electricity-related water use occurs in regions where water availability is more constrained.

In this section, two representations of water stress are used for different analytical purposes. are used to describe the underlying physical water stress conditions at the facility and power plant levels. In contrast, a generation-weighted water stress metric is used at the eGRID level, where each power plant's baseline water stress scores (bws_raw) is weighted by its share of total electricity generation. This weighted metric better reflects the water stress associated with electricity consumption.

4.4.1 Facility-level Water Stress

For LinkedIn's properties (PoP, office, and data center), nearly 30% of properties are located in extremely high (15.8%) or high (14%) water stressed areas, as shown in figure 14. These properties took 40% of total electricity consumption (307,749 MWh out of 778,236 MWh).

Figure 14. Percentage of LinkedIn Leased Sites in Water Stress Areas



While this provides an initial understanding of exposure to water stress, it does not necessarily reflect the water conditions associated with electricity use. This is because electricity is supplied through the grid, and therefore may be generated in regions that differ from where the facilities are physically located.

To better capture the water stress associated with electricity generation, we shift our analysis from facility location to the eGRID region level. For the eGRID analysis, water stress was calculated at the power plant level using Aqueduct baseline water stress scores (bws_raw). Each power plant was assigned a bws_raw score (baseline water stress score) based on its location. To aggregate these plant-level scores to the eGRID region level, we calculated a generation-weighted water stress score. Specifically, each plant's bws_raw value was weighted by its share of total annual electricity generation within the eGRID region. This approach gives greater influence to power plants that contribute more electricity to the regional generation mix. The section below will demonstrate our results.

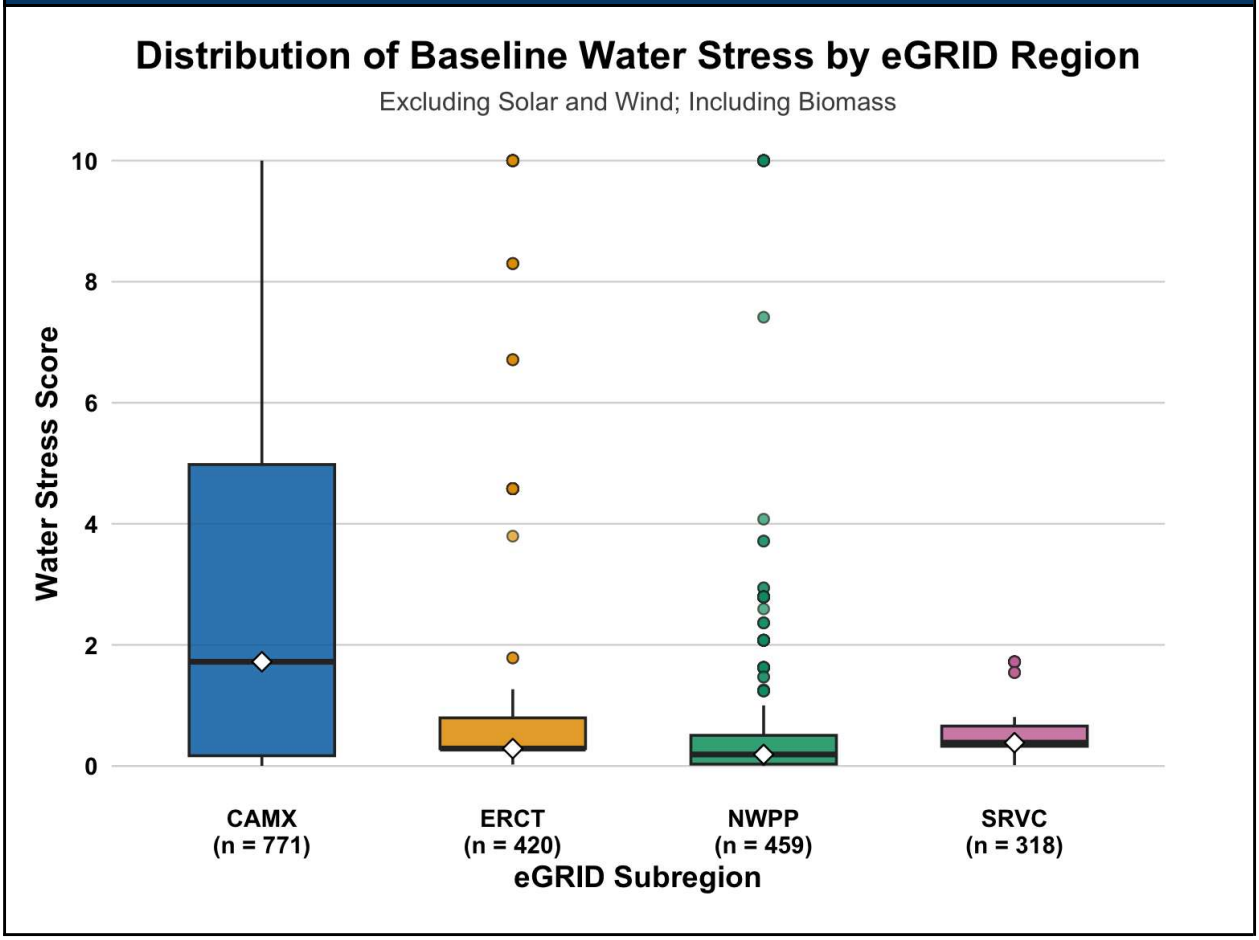
4.4.2 Plant-Level Weighted Water Stress Distribution

Figure 15 presents the distribution of baseline water stress (bws_raw) at the power plant level across the top 4 eGRID regions. These values are not weighted by electricity generation and are used to illustrate the underlying variability of water stress within each region.

CAMX shows the widest distribution and the highest overall water stress values, indicating that many power plants in this region are located in highly stressed watersheds. This supports the finding that CAMX is the most stress-sensitive region in the Aqueduct analysis. ERCT and NWPP have lower median stress values, but both include high-stress outliers, suggesting that some individual power plants are located in highly stressed areas even if the regional average appears moderate. SRVC shows a narrower distribution and lower maximum values, indicating less extreme plant-level water stress compared with the other three regions.

This plant-level variation implicates the importance of not relying only on regional averages. While eGRID-level results are useful for aligning water stress with electricity generation regions, they can mask substantial within-region variation. Detailed summary statistics for the plant-level distribution are provided in Appendix Table A3.

Figure 15, Baseline water stress (bws_raw) statistical distribution of power plant across the top 4 eGRID regions, excluding solar and wind



While the previous analyses are based on the baseline water stress situation in the facilities and plants, they do not address the proportion of water use attributed to each power plant in the electricity generation

Since electricity is supplied via the grid, it is necessary to consider not only where water stress takes place, but also consider the proportion of electricity generated there. To address this, the analysis further shifts to a generation-weighted water stress metric at the eGRID level, which better reflects electricity-related water stress.

4.4.3 eGRID-Level Water Stress and Water Consumption

Figures 16 and 17 combine the understanding of regional baseline water stress and LinkedIn's electricity-related water consumption. Figure 16 shows the spatial overlap between water consumption and weighted eGRID-level water stress, while Figure 17 provides a quantitative comparison across regions. Together, these figures show that the region with the highest physical water consumption is not necessarily the region with the highest water stress.

As the previous result shows, although NWPP has the highest WIT water consumption, its average Aqueduct water stress level is lower than CAMX and ERCT. This suggests that it is a high-volume consumption region, but not necessarily the highest water-stress hotspot under Aqueduct. The result is consistent with WIT, NWPP's high water consumption is largely driven by hydropower-related evaporative losses, while the region's broader water availability conditions reduce its relative stress concern compared with more water-constrained regions.

In contrast, CAMX has lower physical water consumption than NWPP, but it has the highest average baseline water stress among the eGRID regions. This means that even a moderate amount of water consumption in CAMX may be more concerning from a water-risk perspective because it occurs in a region where water resources are already under greater pressure. ERCT falls between these two cases: it does not have the highest water consumption, but it combines moderate water consumption with relatively high water stress.

Therefore, for water consumption, Aqueduct changes the interpretation of the WIT results. NWPP remains important because of its high volume, but CAMX and ERCT become more relevant from a water stress perspective. This distinction is important because water consumption in a lower-stress region and water consumption in a highly stressed region do not carry the same level of concern for water management.

Figure 16. Regional Water Stress and LinkedIn Water Consumption by eGRID Region

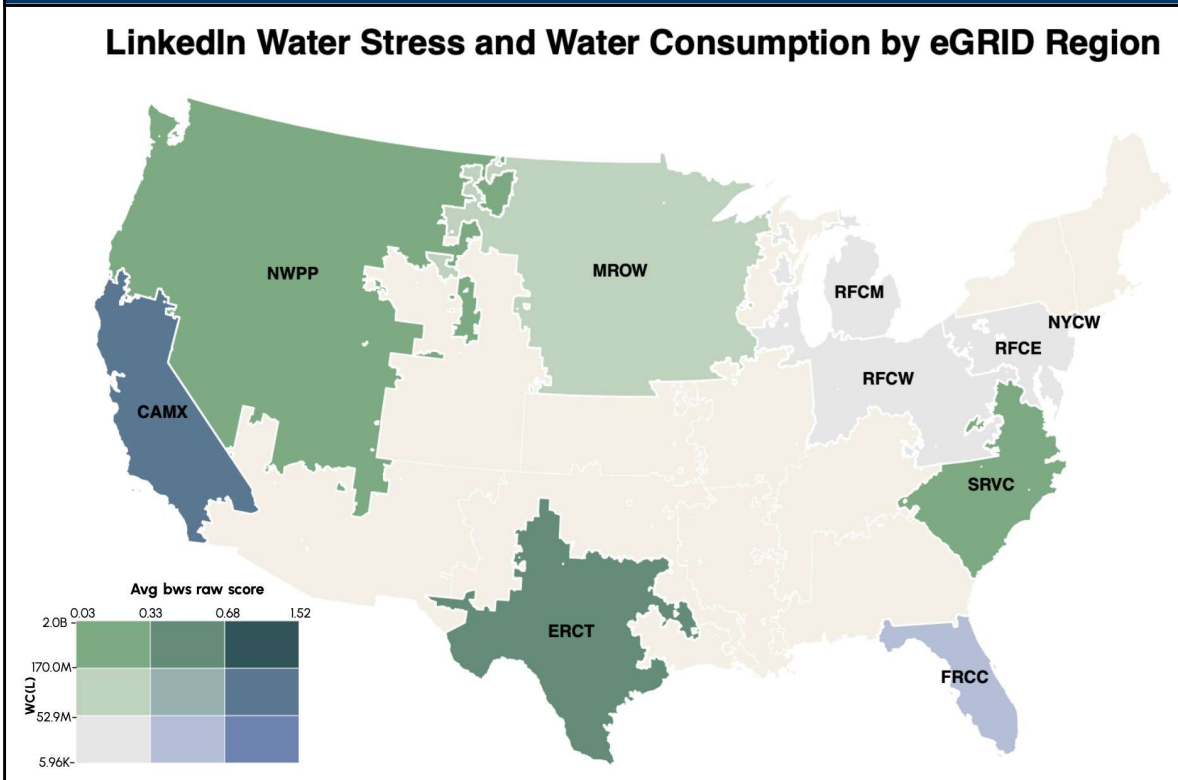
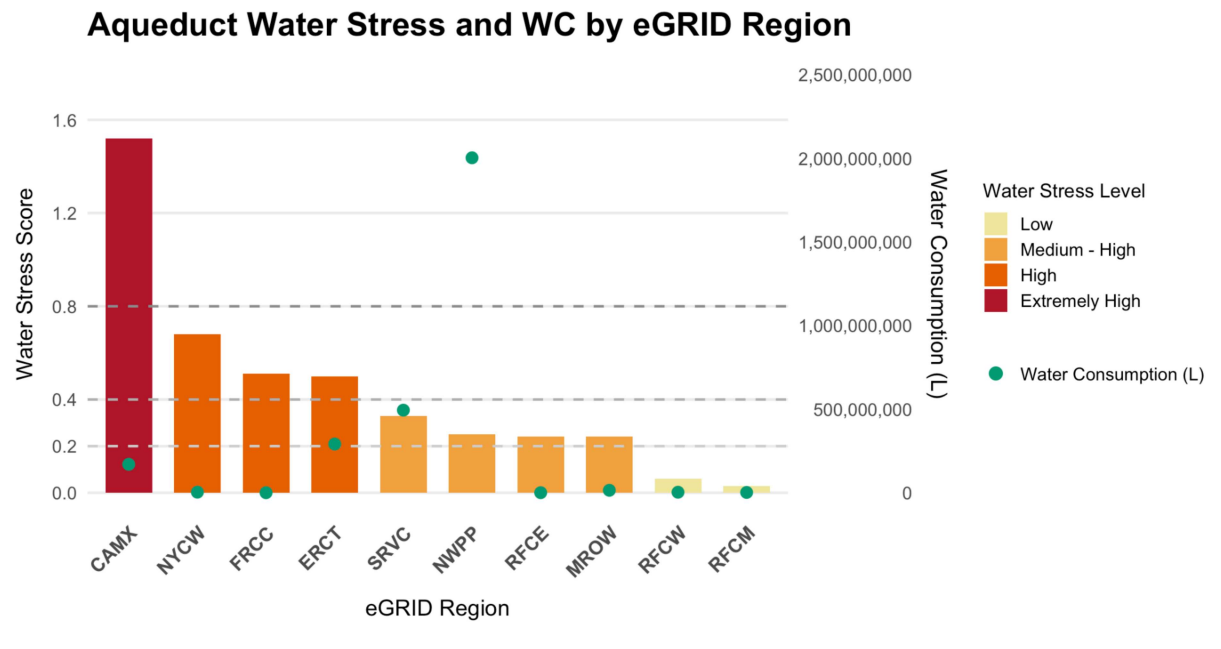


Figure 17, Aqueduct Weighted Water Stress and WIT Water Consumption by eGRID Region. Dashed lines are cutoffs for the water stress level.



4.4.4 eGRID-Level Water Stress and Water Withdrawal

Figures 18 and 19 compare regional baseline water stress with LinkedIn's electricity-related water withdrawal. Unlike water consumption, the withdrawal results highlight ERCT as the most important region. ERCT has the highest WIT water withdrawal and is also located in a region with relatively elevated baseline water stress. This combination makes ERCT a key electricity-related water risk hotspot under the Aqueduct analysis.

The reason ERCT stands out is not only that it withdraws the most water, but that this withdrawal occurs in a region where water resources are already more constrained than in lower-stress regions. As discussed in the WIT results, ERCT's high withdrawal is likely associated with thermoelectric generation and cooling requirements. When this high withdrawal is viewed alongside Aqueduct water stress, ERCT becomes a higher-priority region for water risk management.

SRVC also has high physical water withdrawal under WIT, but its average water stress is lower than ERCT and CAMX. As a result, SRVC represents a high-withdrawal region, but not the highest stress-related concern. CAMX, by contrast, has relatively low physical withdrawal but extremely high water stress. This makes CAMX important from a stress perspective even though it is not the largest contributor to withdrawal volume.

Overall, the withdrawal results show that the highest concern occurs where high water withdrawal overlaps with elevated water stress. Based on this logic, ERCT represents the strongest combined hotspot for withdrawal-related risk, while CAMX represents a stress-sensitive region that should still be monitored despite lower water volume.

Figure 18. LinkedIn Water Stress and Water Withdrawal by eGRID Region

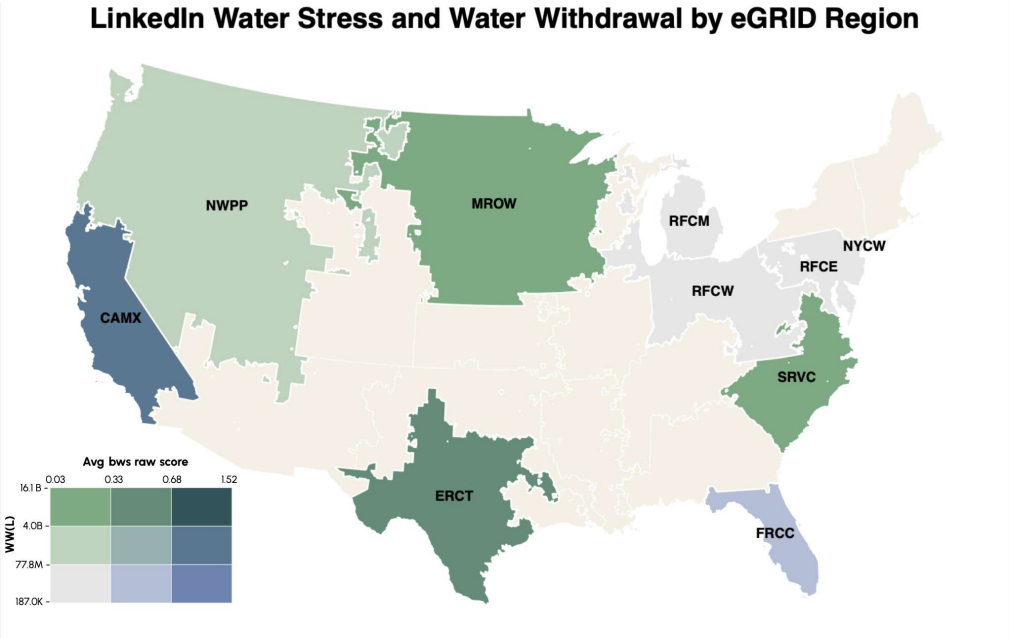
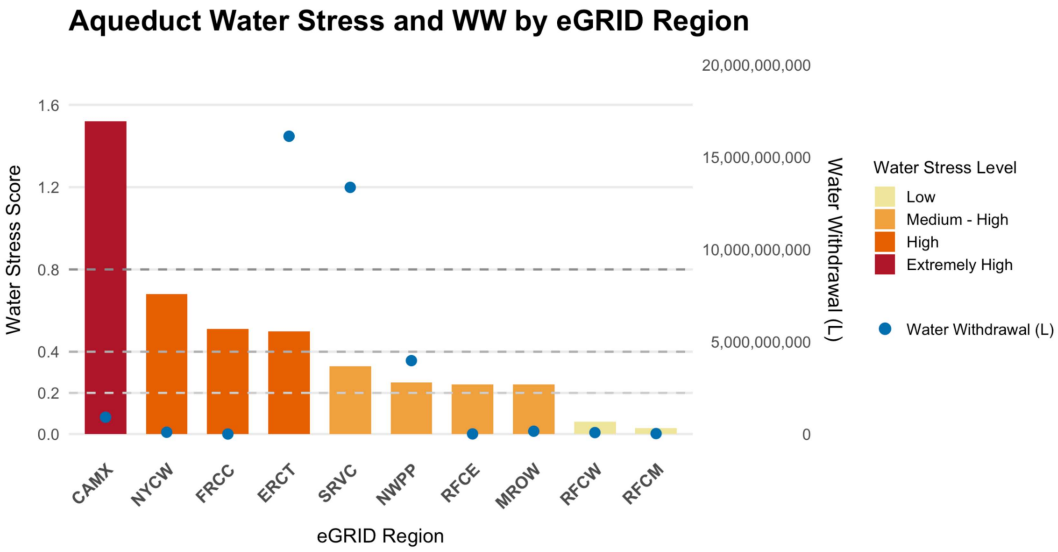


Figure 19, Aqueduct Weighted Water Stress and WIT Water Withdrawal by eGRID Region. Dashed lines are cutoffs for the water stress level.



PART V: Discussion

5.1 Model Recommendations

It is vital for LinkedIn to analyze all three models and understand the results of each. Looking at the Water Impact Tool, there are values that LinkedIn should be aware of. For example, the water consumption factor for the NWPP is extremely high. The generation mix in each eGRID region has a qualitative effect on the water impact tool if you are looking at this particular region. The generation mix is 38.7% hydro in the case of NWPP, meaning it is rich in hydro resources. We would expect this outcome. Both Washington and Oregon have many hydropower plants in this region, so being able to understand that the tool is making the water consumption factor higher than the other regions is crucial. With Texas, they have an even higher disparity between the water consumption and water withdrawal, this could be due to multiple factors. The water withdrawal factor is higher than its water consumption factor by a large margin; even compared to other regions. From our understanding, it could be due to reasons like Texas's generation mix, including steam and installations of their cooling systems. The most important factor to interpret for water consumption and water withdrawal is to examine how many liters of water is in each area and then look at the top 10 power plants in each eGRID region's water consumption. Since, we can not directly correlate which power plant LinkedIn gets their power from, we wanted to look at this as a source of information. Specifically, knowing how much of both withdrawal and consumption is most important for this project.

5.1.1 Analysis of Model Differences

The other two models, Aqueduct 4.0 and AWARE 2.0 for water stress, should be seen as models that could build off each other. However, our results show that there are still some disagreements between the two. The below case study on the NYCW region will help to understand these differences:

Differences between Aqueduct 4.0 and AWARE 2.0

Spatial Resolution (the size of the Grid)

The difference between PCR–GLOBWB 2's grid cells is roughly 25 times smaller in area than WaterGAP's. This allows Aqueduct to pinpoint localized water stress (like a specific county or municipality running dry) with a much higher degree of spatial accuracy than WaterGAP.

Case study AWARE 2.0 vs Aqueduct 4.0: NYCW

The NYCW (New York City–Westchester) eGRID region is one of the most challenging areas in the United States for water footprinting. It illustrates how differences in spatial mapping and methodology between Aqueduct 4.0 and AWARE 2.0 can lead to significantly divergent results.

Spatial Overlap

NYCW is a very small eGRID region that sits at the bottom of the Hudson River watershed.
AWARE 2.0: Uses a custom map that traces the entire natural flow of the river. Groups NYCW within the broader Hudson basin, averaging water availability across upstream

regions with an abundant supply. This dilutes New York City's high demand, resulting in a low scarcity characterization factor (CF).
Aqueduct 4.0: Uses HydroBASINS Level 6 boundaries to isolate the densely populated lower Hudson area, capturing localized demand and assigning "extremely high" baseline water stress.
As a result, NYCW appears to have low environmental impact (AWARE) but high business risk (Aqueduct) due to differences in spatial scale.

Coastal Boundary Sensitivity
New York City's geography –an archipelago surrounded by estuaries, tidal straits, and the Atlantic Ocean– introduces additional complexity.

AWARE and Aqueduct draw their coastline borders slightly differently. If the coordinates for a thermal power plant in the NYCW eGRID region are situated right on the edge of the water (like the Ravenswood Generating Station in Queens), one map might categorize it as being inside a freshwater river basin, while the other map's border might be drawn a few pixels differently, categorizing that exact same plant as being in the ocean. This distinction is critical because if a facility is categorized within an ocean polygon, it may be assigned a zero freshwater scarcity factor, since seawater is not considered a limited freshwater resource.

Saline Water Use
Power plants in the NYCW region predominantly use once–through cooling systems that withdraw large volumes of water from the Hudson River estuary and the East River, both of which are highly saline.

Because both models assess freshwater scarcity only, they do not penalize saline water use. However, the Excel model applies AWARE factors to total water withdrawals from eGRID (including saline water), leading to an overestimated water footprint.

Key Takeaway
Differences in spatial scale, coastal boundary definitions, and treatment of saline water explain why NYCW simultaneously appears as high risk (Aqueduct) and low impact (AWARE), while also revealing potential overestimation in the footprint calculation.

We recommend that, if there is a disagreement between the two models, LinkedIn should move forward with the Aqueduct tool. This is because LinkedIn already has prior experience with the methodology and it is more intuitive than the AWARE model.

5.2 Alternative Approaches; Plant-level Estimates and Modeling in LinkedIn's Scope 2 Water Use Beyond the USA

The United States is extremely data rich and has extensive research that creates different models. In other countries they may not be as lucky as we are. To start, we viewed two other methodologies before ultimately deciding on the water impact tool. We observed GREET (40B–SAF0GREET) and eGRID region water consumption factors. GREET is a lifecycle analysis model from Agronne National Laboratory that utilizes environmental impact of fuels

and energy systems (GREET, 2025). GREET's main research is not water consumption, but the factors are still in the Excel spreadsheet as a smaller part of it. GREET's lifecycle analysis models dive into transportation and factors for environmental externalities. GREET has NERC as a regional grouping which is a less granular grouping then the eGRID regions we are using. GREET releases data annually, updating their factors to ensure they are up to date (GREET, 2025). The summary of eGRID region water consumption factors which utilized eGRID regions as its spatial resolution was the other. Specifically the study utilizes 2014 as its baseline year for eGRID regions. The goal of the report was to shift the focus from national averages to the importance of geographic specifics in water footprinting. The goal of this method was to look past the national average and show the importance of specific geographic water footprinting.

These two models were adequate but the one we want to highlight above all is our work over the summer of 2025. Due to LinkedIn being a worldwide company, they will have to look at areas around the world next. Like stated earlier, LinkedIn is already at 97% of electricity consumption in the USA. It is important to still obtain that missing 3% and a bottom up approach would be the best option to achieve it. This is why continuing on with our linear model that we created over summer could be the best option. To start the process we cleaned the data, which included the eGRID 2023 data and the 2023 EIA water thermoelectric cooling water data. The cleaning included making the EIA data annual, since it was monthly. The reasoning behind this is because the eGRID dataset is annual data, so we wanted to ensure that both datasets were matched. Once finished with cleaning, the goal is to be able to combine the data and start the linear model from there in RStudio. As well as making it yearly, we cut out the negligible parts of the columns for what we were looking for. When putting it into Rstudio we decided on combining the data then trying to find the best statistically significant data. We utilized both the summarized version and detailed version of the EIA to make sure that we got the highest significance possible.

When looking at the results we tried to find significant p-values that would tell us which categories would be the most consequential. We first had to combine the two cleaned data sheets together to ensure that we have all the possible labeling. A lot of the best data pieces that we acquired were for water withdrawal, but at the same time it could be due to a couple different factors. For example, after extensive testing we wanted to see if breaking them up by fuel source will make the data more significant, which it did. The issue though was that some of the p-values were around the .7– .9 range in some areas due to factors such as not having a big enough sample size. Some of the most significant combinations for the water consumption linear models for the combined data were combinations of the following: boiler retirement year, generator retirement year, gross generation from steam engine and net generation from stream engines. This makes sense because older models for boilers and generators are less efficient. The combined data for the water withdrawal values had categories like gross generation from steam engines, boiler retirement year, generator retirement year and latitude. This further states the same idea as the one above for efficiency standards of technology and latitude is an interesting addition as well. This suggests that some of the statistically significant relationships could be transferable to regions outside of the US, even though the data we utilize is US specific. When we were looking at the methodologies for WIT, we saw that they utilized the same data sources like EIA thermoelectric cooling data, eGRID data, and then two different EIA sources. We believed this is better compared to GREET and the other eGRID methodology due to its variance along with actually having water withdrawal. A large importance for us was that we wanted to have both

water withdrawal and water consumption together if possible. This is why a bottom up approach should be implemented for the rest of the world, since it is similar to what the water impact tool accomplished.

5.3 Towards Water Positivity → High-Level Recommendations

As LinkedIn begins to utilize this model there are some recommendations we want to advise on. The first recommendation is that they should reduce the energy demand of their data centers; this means trying to become more efficient. They should begin with high impact regions, more specifically the most water intensive. For example, start with ERCT and proceed down from there. Another recommendation is to reduce the water intensity of LinkedIn's electricity use by prioritizing low water sources like solar and wind. The caveat with this though is that market based accounting was not factored in, but could be incorporated with more research in the future. LinkedIn should also partner with utilities to prioritize water efficiency within power plants. They can improve cooling technologies and move the grid away from water intensive power plants. These two recommendations together could mean higher upfront costs, but the investments in this infrastructure could help with reducing long-term water related issues. Lastly, LinkedIn needs to utilize this methodology as a source for evaluating where to expand their data center operations, including where to seek public input (Rushforth et al., 2019). Being cognizant of the areas that are utilizing an abundance of water for agriculture and where water costs a premium is significant for this expansion.

5.4 Limitations and Future Research

We made a couple assumptions throughout this model. The first assumption was that data centers consume an electricity mix proportional to the average grid generation mix of the region. We also assumed that when there were 9999 values for the Aqueduct tool that then it would be the highest factor possible for the bws_raw score, which was 10. Finally one more assumption was that the Water Impact Tool for LinkedIn's facilities used electricity over a full 24 hour period, rather than only in the daytime or nighttime. There were three different ways we could have done it and they all were extremely similar but actually being able to know if it was daytime, nighttime, or 24 hour could have made it more granular.

Any methodology has its limitations that come along with it, and this one is no different. The first limitation is the spatial mismatch between watersheds and balancing authorities for the AWARE method. We do not have data available to track LinkedIn's purchased electricity back to the original power plants generating it. Spatially heterogeneous water impacts are obscured by all of the aggregation that happens in the grid. One example of this limitation is having to use an eGRID region GIS file for our AWARE 2.0 model even though we were trying to get more spatially resolved by using a balancing authority GIS file.

Another limitation that happened in this project is excluding energy storage which could be part of scope 2 water usage. Water impacts from energy storages vary significantly, especially depending on the type of technology and its cooling and management requirements (Rezk et al., 2025). Technologies like flywheels and battery energy storage generally have low water use, meanwhile systems like thermal energy storage and compressed air storage have higher water use (Pan et al., 2018). This is due to technologies like thermal energy storage and compressed air storage that have cooling technologies that rely on more water-intensive cooling technologies, specifically wet cooling systems (Rezk et al., 2025). Pumped storage hydro is distinguished for

its large consumption of water. Incorporating energy storage may not make a significant difference for the results, but it can improve the model by becoming more specific.

We also did not touch on factors like water quality, human health and ecological effects. Like stated above there are different ways to implement a project like this. We went down the route of water consumption, withdrawal and stress; but could have looked into factors like these as well. We did not add this because to start we thought that these three factors would be more technically sound, instead of worrying about the social sides of things right away. If we had more time we would most likely have started to add in the factors above.

Even though there were limitations within the model there are also some limitations that LinkedIn deals with. Some things are out of their control such as it not being realistic for them to have self sufficient power. Data centers take a lot of power to operate, and it is extremely difficult to be fully self-sufficient in their case as of right now. There are also limited resources like space. There are only so many areas they can site as there is a higher dependence on data centers. Today, this is an issue until there are further policies to open up free land and factors like proximity to fiber optic cable infrastructures. When they do site these data centers, they are joining in on pre–existing grids, so they have to deal with the current generation mix of that grid. This goes into detail with the idea above regarding self–sufficiency; companies have to deal with the impacts that come with the generation mix.

Finally, there are some future directions to take this project, like earlier when we touched on moving outside of the USA. Since LinkedIn is a global company, they need to expand the analysis worldwide, even if that means utilizing a linear model like stated earlier. The linear model is an exceptional method that can help LinkedIn reach their goals. After that they should move on to scope 3 methodologies because semiconductor chip manufacturing is extremely water intensive (No, 2025). Scope 3 water use is the last step for LinkedIn to see its full water footprint, so they have to move there next to reach beyond their goals. Finally, also exploring market-based accounting approaches when it comes to water. We barely touched the surface on it, so we highly encourage doing a deeper analysis.

PART VI: Conclusion

We assessed LinkedIn's purchased electricity's scope 2 water use to ultimately create a model that they can utilize. We built a model that has water scarcity, water consumption and withdrawal factors. This was not the only way to go about doing this project, but we as a team found this to be the one that best matched what LinkedIn's vision entailed. For water consumption and water withdrawal intensity factors we came to the conclusion that the Berkley Labs Water Impact Tool was the most suitable for what we were looking for. For water scarcity, we took a different approach where we utilized two different methodologies, one being AWARE 2.0 and the other being the Aqueduct tool. We found that some of the most scarce regions are primarily in states that are commonly known for water scarcity, like California. Meanwhile, the water consumption and water withdrawal factors oftentimes differed depending on their balancing authority, due to the fact that they all utilize a different generation mix and have different factors that coincide with that mix. For example, when looking at NWPP's generation mix, they utilize hydroelectric power the most out of anyone, so they will have a large water consumption factor. This project showed LinkedIn the importance of understanding their water footprint to reach their goals as a company by 2030 and beyond. Overall, understanding the full scope of water use from data centers is vital for the future of the world as we begin to rely more heavily on it. Utilizing this as a stepping stone to further LinkedIn's research into their scope 3 water use will be the next step to achieving their 2030 goals. This application is just for the United States, but there are resources within our project that can be further utilized when LinkedIn expands globally. We laid the groundwork for the linear model if they want to utilize that or even utilize the water consumption factors from the GREET model. For water scarcity AWARE and aqueduct are worldwide as well, so it would be more towards the water consumption and water withdrawal where they have to figure out what they want to do. We recommend the linear model more than GREET, because it closely aligns with the Water Impact Tool's datasets. As a society, we are growing in demand for data centers, and so is the desire to understand and mitigate the effects they have on the environment. Our project is just a small step in a broader vision of how data centers will affect the world around us and how we as a society can help figure out what the future holds. It has always been in our hands; we just need to take the time to do the research and processes necessary to understand.

Appendices

Below tables show the fuel mix of the top 4 eGRID regions where LinkedIn's facilities are located.

Table A1. From right to left: Percentage of NWPP fuel mix of electricity generation, ERCT fuel mix of electricity generation, SRVC fuel mix of electricity generation

	NWPP Fuel Mix	ERCT Fuel Mix	SRVC Fuel Mix	CAMX Fuel Mix
Fuel Type	Percentage (%)			
Hydro	38.74	0.1	1.38	14.1
Gas	24.56	48.77	41.5	41.5
Coal	16.84	13.11	9.68	2.1
Wind	11.19	22.68	2.75	6.48
Solar	2.41	5.54	3.76	20.02
Nuclear	3.1	8.53	39.98	8.04
Biomass	1.19	0.8	2.34	3.63
Geothermal	1.73	0	0	2.88
Oil	0.07	0.03	0.12	0.48
Other Fossil (OFSL)	0.07	0.04	0.02	0.77

Every eGRID region produces a different amount of electricity generation (MWh). We made a total annual summary by fuel types, and the explanation of each category is shown below:

1. The total annual electricity generation (MWh) includes electricity generation of all power plants in 10 eGRID regions where LinkedIn's facilities are located.
2. Total annual fossil fuel (FF) Generation (MWh) includes Coal, Gas, OFSL, OIL, and nuclear.
3. Total annual fossil fuel + hydro + Geothermal includes Coal, Gas, OFSL, OIL, nuclear, hydro, and geothermal.
4. Total renewable energy generation includes biomass, solar, and wind.

Table A2. Summary Table of Electricity Generation by Fuel Type in Each eGRID Region

eGRID Region	Total Gen (MWh)	Total FF gen (MWh)	Total FF + Hydro + Geothermal (MWh)	Total Renewable Gen (MWh)	# of Linked in Data Centers	LinkedIn ElectricityUse (MWh)
RFCW	523,897,570	332,985,042	487,407,088	40,092,036	0	1,586
ERCT	476,903,914	299,148,205	340,288,055	137,002,058	5	303,320
SRVC	319,245,154	159,049,785	291,084,629	31,782,149	5	269,588
RFCE	284,883,586	166,785,942	273,624,536	11,329,908	0	123
NWPP	269,009,106	111,730,289	226,199,229	148,410,914	4	166,213
FRCC	249,148,964	194,431,911	231,178,887	16,425,690	0	4
MROW	240,624,647	116,550,664	145,360,841	104,845,228	0	3,821
CAMX	221,575,476	99,941,923	156,878,790	102,858,892	1	30,598
RFCM	91,629,583	71,982,429	80,945,201	10,231,839	0	451
NYCW	34,602,448	34,180,653	34,180,653	34,399,944	0	2,530
Total	2,711,520,448	1,586,786,843	2,267,147,909	637,378,658	15	778,236

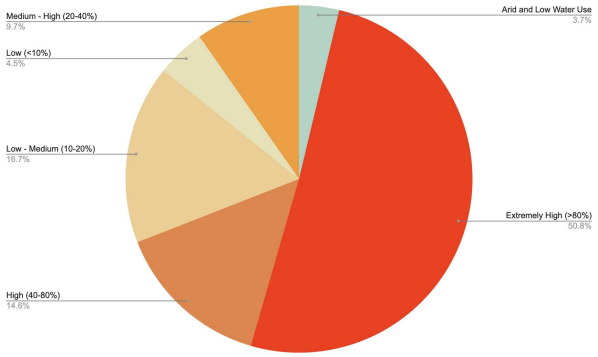
Table A3, Summary table of water stress score (bws_raw).Max, Min, Median of Top 4 eGRID Regions

eGRID region	Max (bws)	# of Max	Example Max Plant	Median (bws)	Median Plant	Min (bws)	# of Min	Example Min Plant
CAMX	10	94	AT&T – San Diego Trade Street	1.72	Aera San Ardo Cogen Facility	0.00214	3	Navy Yard CHP
ERCT	10	17	Bakke	0.29	Air Liquide Bayport Complex	0.02356	5	Valero Refinery
NWPP	10	12	Bloomington Power Plant	0.22	Boulder Park	0.00024	1	John Day
SRVC	1.72	7	Albemarle Hospital Unit	0.38	Bridgewater	0.01338	2	Cliffside Steam Station

Below pie charts, Figure A1 - Figure A12, represent the percentage of eGRID power plants which are located in Aqueduct water-stressed (bws_raw) areas. Each region has three categories of fuel mix.

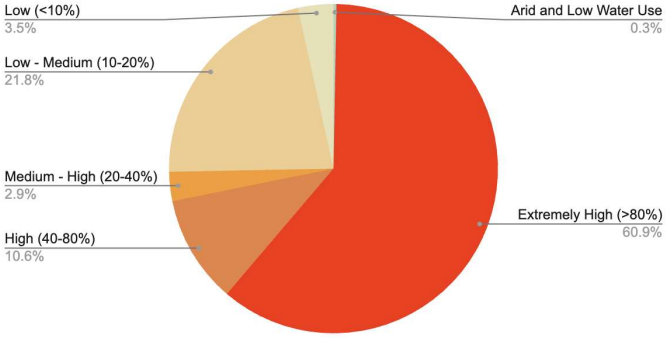
CAMX

Figure A1. CAMX Power Plants in Water Stressed Areas



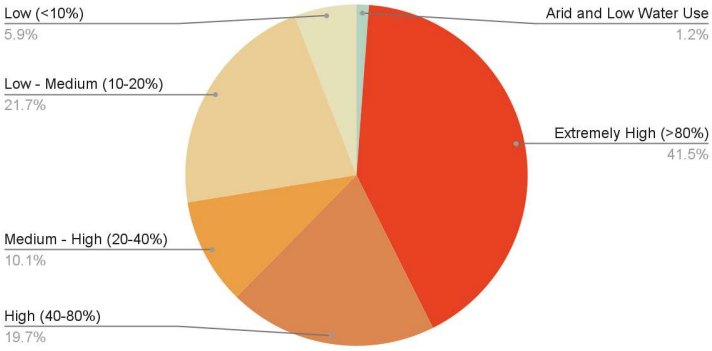
Total Net Generation (MWh): 221,575,476

Figure A2. CAMX FF Power Plants in Water Stressed Areas



Total Fossil Fuel Generation (MWh): 99,941,923

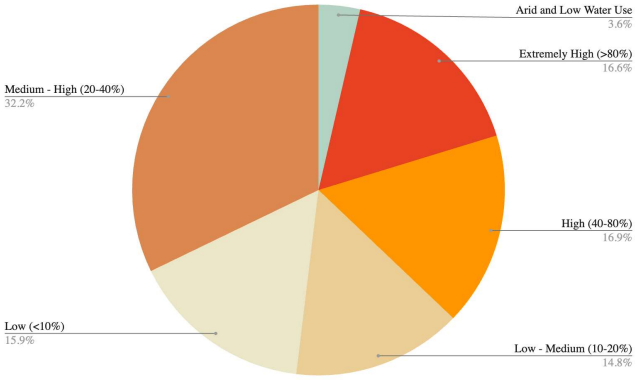
Figure A3. CAMX Total FF + Hydro + Geothermal Power Plants in Water Stressed Areas



Total FF + Hydro + Geothermal Generation (MWh): 156,878,790

ERCT

Figure A4. ERCT Power Plants in Water Stressed Areas



Total Net Generation (MWh): 476,903,914

Figure A5. ERCT FF Power Plants in Water Stressed Areas

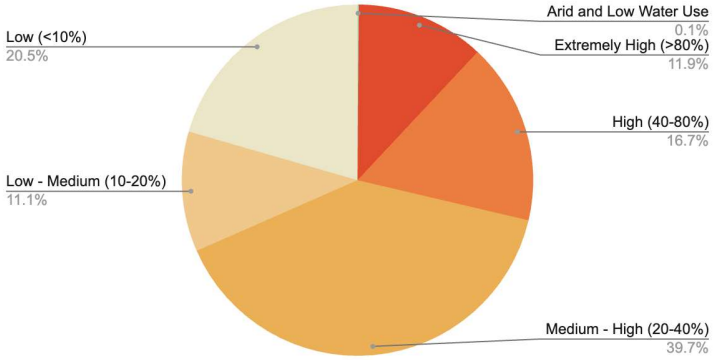
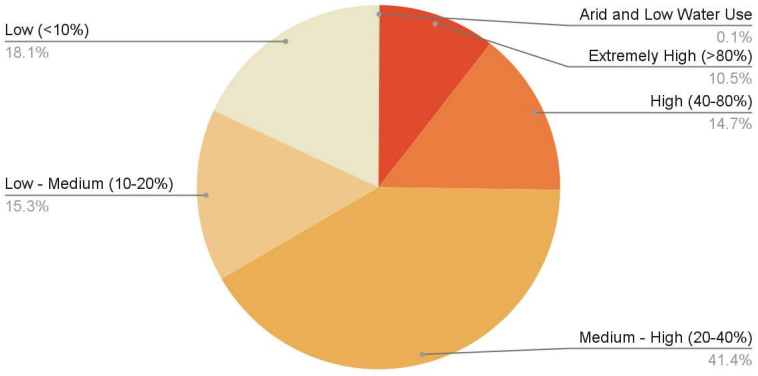


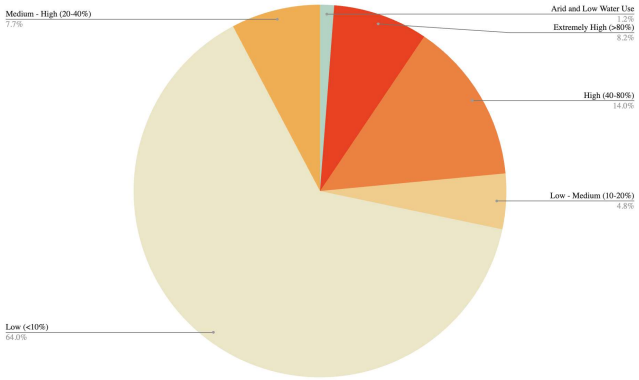
Figure A6. ERCT Total FF + Hydro + Geothermal Power Plants in Water Stressed Areas



Total FF + Hydro + Geothermal Generation (MWh): 340,288,055

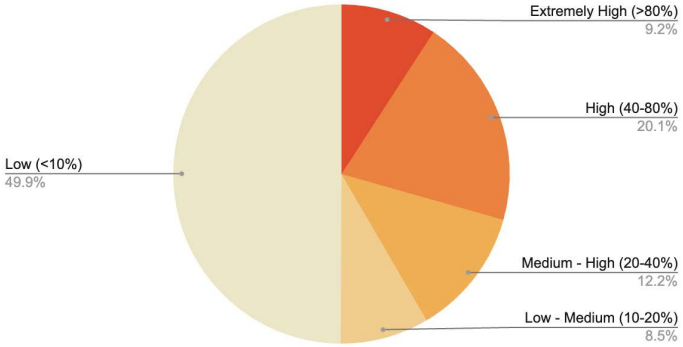
NWPP

Figure A7. NWPP Power Plants in Water Stressed Areas



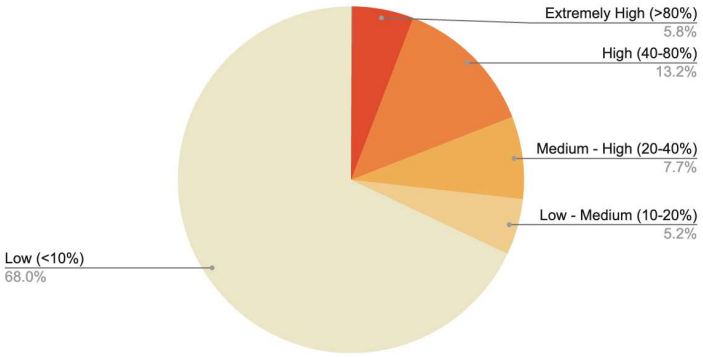
Total Net Generation (MWh): 269,009,106

Figure A8. NWPP FF Power Plants in Water Stressed Areas



Total FF Generation (MWh): 111,730,289

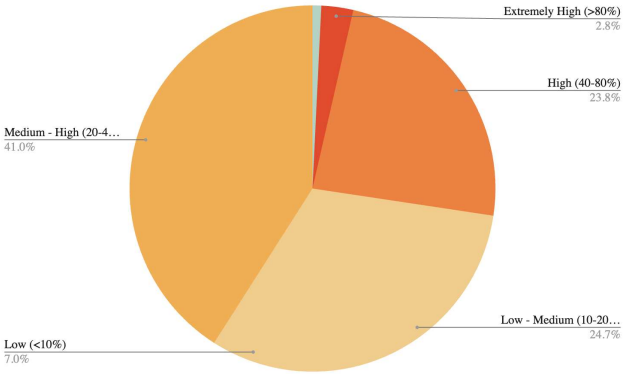
Figure A9. NWPP Total FF + Hydro + Geothermal Power Plants in Water Stressed Areas



Total FF + Hydro + Geothermal Generation (MWh): 226,199,229

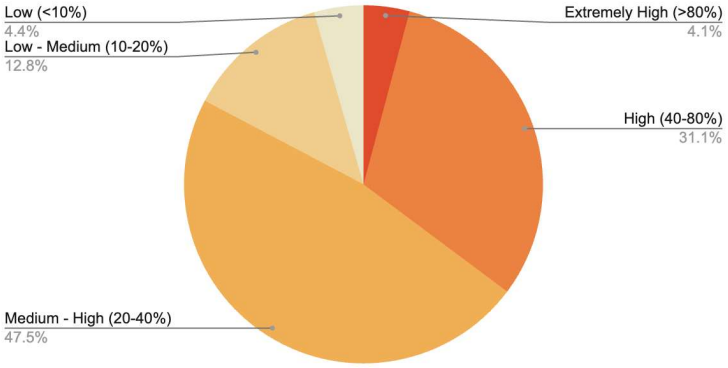
SRVC

Figure A10. SRVC Power Plants in Water Stressed Areas



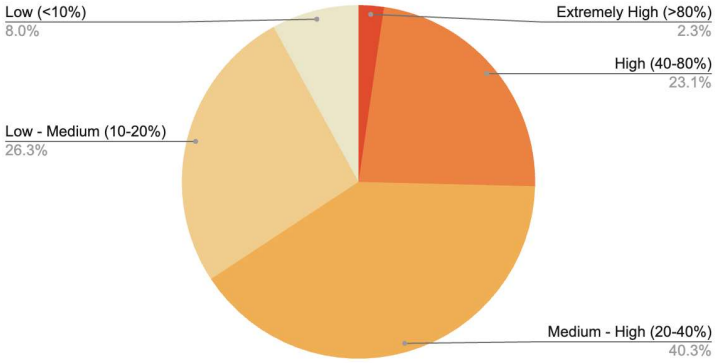
Total Net Generation (MWh): 319,245,154

Figure A11. SRVC FF Power Plants in Water Stressed Areas



Total Fossil Fuel Generation (MWh): 159,049,785

Figure A12. SRVC Total FF + Hydro + Geothermal Power Plants in Water Stressed Areas



Total FF + Hydro + Geothermal Generation (MWh): 291,084,629

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