Title

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Publication Date

2025-06-23

DOI

10.20357/B7CC9K

Peer reviewed

BERKELEY LAB

Buildings and Industrial Applications Department

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Addressing Risks through New Approaches and Technologies

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May 2025

https://doi.org/10.20357/B7CC9K

This work was supported by the Industrial Technologies Office at the U.S. Department of Energy under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231.

Advancing Manufacturing Water Resilience: Addressing Risks through New Approaches and Technologies

Prepared for the
Industrial Technologies Office
U.S. Department of Energy

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Submitted December 2023; published May 2025

The work described in this study was funded by the Industrial Technologies Office at the U.S. Department of Energy under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231

Preface

This report was prepared for the U.S. Department of Energy's Industrial Technologies Office to help identify technology development and deployment needs for manufacturing water conservation and management. It focuses on risk mitigation to enhance resilience. It was submitted to DOE for publication in December 2023 and finalized as a Berkeley Lab report in May 2025. This report synthesizes and expands upon a collection of peer-reviewed works on the topic published by report authors, cited below.

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Acknowledgements

This report was prepared and authored in part by Lawrence Berkeley National Laboratory for the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, Industrial Technologies Office under Contract No. DE-AC02-05CH11231.

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This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy under Contract No. DE-AC36-08GO28308. The views expressed herein do not necessarily represent the views of the DOE or the U.S. Government.

This manuscript has been authored in part by UT-Battelle, LLC, under contract DE-AC05-00OR22725 with the U.S. Department of Energy. The United States Government retains and the publisher, by accepting the article for publication, acknowledges that the United States Government retains a non-exclusive, paid-up, irrevocable, world-wide license to publish or reproduce the published form of this manuscript, or allow others to do so, for United States Government purposes.

The authors would like to acknowledge Joe Cresko at DOE, who was instrumental in guiding and supporting this work. They would also like to acknowledge the following internal and external reviewers, whose contributions improved the clarity and quality of this report:

Rishabh Bahel (Nestlé)
John Hill (Cleveland-Cliffs)
Bill Hoffman (Hoffman & Associates, LLC)
Landon Marston (Virginia Tech)
Ariel Miara (NREL)
Mark Philbrick (DOE)
Michael Rinker (DOE)
Jennifer Stokes-Draut (LBNL)
Kimmai Tran (DOE)
Reshmina William (Isle Utilities)

We are also grateful to Caroline Dollinger (Energetics), who assisted with coordination and publication, Amy Pevzner (LBNL) for graphics support, and Tiana Nishime (LBNL), who assisted with report editing.

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Acronyms and Abbreviations

AIC	Akaike Information Criterion
AMO	U.S. DOE's Advanced Manufacturing Office
ANL	Argonne National Laboratory
BEA	U.S. Bureau of Economic Analysis
BG	billion gallons
BGD	billion gallons per day
BOD	biochemical oxygen demand
CDP	Carbon Disclosure Project
CFS	Commodity Flow Survey
CGE	computable general equilibrium
DHS	U.S. Department of Homeland Security
DMR	EPA Discharge Monitoring Report
DOE	U.S. Department of Energy
DR	Demand Response
eCFR	Electronic Code of Federal Regulations
EIA	U.S. Energy Information Administration
EIO-LCA	economic input-output life cycle assessment
EPA	U.S. Environmental Protection Agency
FEMA	Federal Emergency Management Agency
GDP	gross domestic product
GHG	greenhouse gas
GRP	gross regional product
GRACE	Gravity Recovery and Climate Experiment
HUC-8	8-digit Hydrologic Unit Code
IACs	Industrial Assessment Centers
ICIS	Integrated Compliance Information System
IEDO	DOE's Industrial Efficiency and Decarbonization Office (previously AMO)
INPLT	DOE's In-Plant Training
IoT	internet of things
IPCC	Intergovernmental Panel on Climate Change
ISO	International Standards Organization
IWS	Canadian Industrial Water Survey
kgal	thousand gallons
LBNL	Lawrence Berkeley National Laboratory
LCA	life cycle assessment
LSCF	loss in sensible cooling factor
MAD	mean absolute deviation
MECS	Manufacturing Energy Consumption Survey
MG	million gallons
MGD	million gallons per day
MQL	minimum quantity lubricant-in-compressed air
MWFs	metalworking fluids
MWh	megawatt-hour
MRR	material removal rate
NAICS	North American Industry Classification System
NASA	National Aeronautics and Space Administration
NEMS	Nestle Environmental Management System
NPDES	National Pollutant Discharge Elimination System
NPP	National Pretreatment Program

NREL	National Renewable Energy Laboratory
OCE	otherwise curtailed electricity
ORNL	Oak Ridge National Laboratory
PES	payment for ecosystem services
PCA	power control area
POTWs	publicly owned treatment works
PWP	Plant Water Profiler
R&D	research and development
RCP	Representative Concentration Pathway
ReEDS	Regional Energy Deployment System
SCADA	Supervisory Control And Data Acquisition
SWUM	U.S. Census Bureau Survey of Water Use in Manufacturing
TRI	Toxics Release Inventory
TSS	total suspended solids
UNDRR	United Nations Office for Disaster Risk Reduction
USEEIO	U.S. Environmentally-Extended Input-Output
USGS	U.S. Geological Survey
VCI	value chain indices
VMP	value of marginal product
Water INPLT	Water In-Plant Training
WaSSI	Water Supply Stress Index
WBCSD	World Business Council for Sustainable Development
WRI	World Resources Institute
WTP	willingness to pay

Executive Summary

Water is indispensable in manufacturing operations, and many manufacturers operate on the assumption that water of sufficient quality and quantity will be available whenever and wherever needed. As such, the importance of water to this sector has been overlooked, despite its critical importance for operations and meeting production demands, due to perceived sufficient availability and low cost of water to manufacturers. However, the situation is changing as water-related risks are markedly increasing due to aging infrastructure as well as climate change and unabated resource exploitation, which alter global and regional water cycles and characteristics. These changes are occurring against a backdrop of intensifying competition from other sectors for scarce and/or unevenly distributed water resources and changing trends in water needs. Section 1 of this report explores those risks in the U.S. context, while the remaining sections detail the work needed to advance the resilience of manufacturing water supplies to these changing risks by filling critical data gaps, re-evaluating the value of water to manufacturers, and advancing opportunities for novel technologies and analyses. The intended audience for this report is broad, including manufacturers, decision makers, researchers, and policymakers.

Section 1 gives objectives for this report before providing an overview of U.S. manufacturing water risks and defining water resilience in manufacturing. It finds that water and manufacturing are inextricably linked, affecting the day-to-day critical operations of a manufacturing facility and the broader watershed and water infrastructure of which the facility is a part. Manufacturing industries use water for critical functions, including processing, cooling, cleaning, mass transport, dissolution/precipitation, irrigation, and fire suppression. However, despite water's criticality, its use and discharge characteristics in manufacturing are poorly tracked and understood, leaving facilities vulnerable to natural and human-caused water-related hazards. However, some firms do attempt to assess and mitigate various aspects of their water criticality and risk. Their assessments rely on surveys and past exposures to disruptions, and mitigation measures range from setting water conservation goals to factoring into business decisions a price of water much higher than their cost to procure it. Section 1 also articulates key research questions aimed at increasing manufacturing resilience and lessening the impacts of manufacturing water use on watersheds.

One main hindrance to greater uptake of water conservation and related technology development is the lack of sufficient water-related data that is characteristic of the manufacturing sector. Specific gaps include data on manufacturer water use uptake, recirculation, and disposal, water use intensities, and water quality requirements for manufacturing and supporting processes. This paucity of data makes it impossible to evaluate the likelihood and potential impacts of unforeseen risks, preventing either mitigating or adapting to them. Additionally, it leads to uncertainty when examining water conservation technology needs and impacts—leaving research, development, demonstration, and deployment efforts without guidance for prioritizing efforts.

To address and quantify this uncertainty, Section 2 of this report describes existing manufacturing water use estimates to support risk analysis, emphasizing where data related to both water volume and quality are needed. It also underscores that knowledge of water quality requirements is critical to understanding opportunities for on-site water reuse. Section 2 establishes that reliable, usable, and accurate water data for plant and sectoral-level water use does not currently exist for the U.S. manufacturing industry. Numerous past methods have been used to estimate water use within manufacturing plants, but they are inconsistent with one another and present only a snapshot in time that does not reflect changes in industry. Recent papers summarized in this section have proposed new data requirements for performing risk and resiliency analyses to determine the U.S. manufacturing sector's risk with respect to water use.

Figure ES.1 graphically displays the current state of manufacturing water data as discussed in this report, showing that facility-level water data are largely unavailable. A dataset with enough information to inform policymaking and economic decisions would provide a multitude of benefits, including leading manufacturers to implement process improvements and increase resilience while lessening the impacts of water use and discharges on local watersheds, environments, and communities.

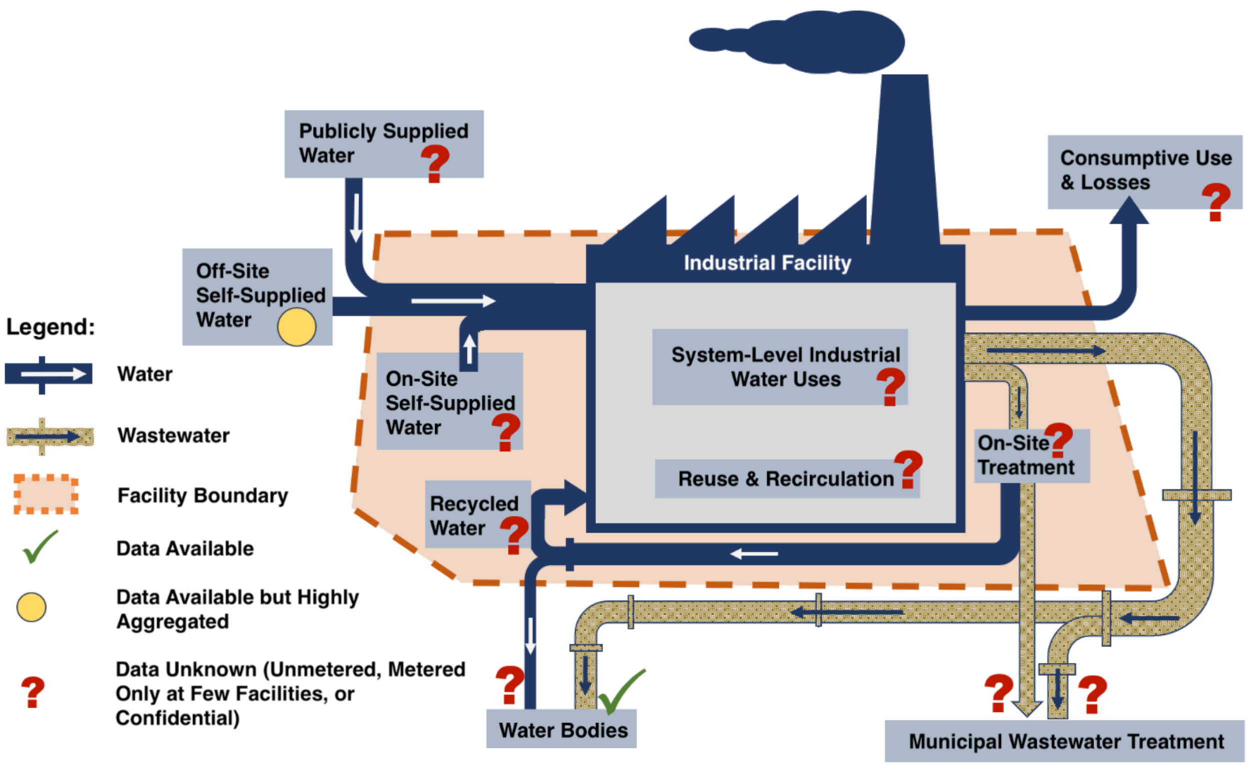

Figure ES.1. Current state of manufacturing water data
McCall et al. (2021)

Section 2.4 of this report summarizes the challenges of collecting water flow data at a manufacturing plant. Water flow submetering is needed at the subsystem level to conduct an accurate water mass balance, which can identify inefficient water uses or unintentional losses. Challenges to such submetering include difficulties related to installation as well as their capital cost, which may seem unattractive to manufacturing facilities that have not yet monitored water use and consumption. However, more granular and comprehensive data would enable a more representative and accurate evaluation of water use characteristics throughout the manufacturing sector and support analyses such as those presented in Section 2.5 that describe physical and thermal water risks to U.S. manufacturers. As an example, Section 2.5.1 shows that the primary metals, fabricated metals, transportation equipment, petroleum and coal products, and plastics and rubber manufacturing subsectors are at the greatest risk of physical water shortages based on concentrations of water intake in water-stressed regions. Section 2.5.2 finds that for 33 manufacturing facilities evaluated, a 0.5°C increase in surface water temperatures would lead to a 2%–12% reduction in cooling capacity, while a 3°C increase would lead to a 15%–72% reduction in cooling capacity. These results demonstrate that physical and thermal risks to manufacturing water supplies are consequential.

In part, water has been relegated to the background of operational concerns because it makes up an insignificant share of total manufacturing costs. In addition, manufacturers' primary objective is to maximize profits; sustainable resource use is a lower priority. As such, the current economics of water in manufacturing generally do not encourage conservation or efficiency beyond no-cost actions. However, the accelerating pace of climate change has considerably increased the probabilities of restricted water access—or indeed, loss of access—and compromised water quality.

Section 3 demonstrates that the economic value of water is significantly undervalued today, with water prices often not even covering the direct costs of supply. It finds that the manufacturing industry has often considered water too cheap to conserve. Because the price of water is negligible relative to total manufacturing costs, it is difficult to justify implementing water conservation technologies for financial reasons alone. In fact, the full value of water to manufacturers far exceeds the price of water. Recent work has identified the "true cost of water" as the total costs required to source, treat, and use water, as well as those associated with wastewater disposal. This more robust valuation of water could be estimated at manufacturing plants with the appropriate data collection capabilities. However, this rarely occurs given the lack of awareness of the extent to which water is undervalued, as well as the tools needed to quantify the true cost. Moreover, many facilities lack the necessary data collection capabilities in the first place. However, the "true cost of water" still excludes the costs of retooling or establishing an alternative water supply and the indirect and opportunity costs related to lost production and environmental externalities inflicted on the watershed and other water users. In addition, it is challenging to quantify the costs of climate-related risks to water because they require more advanced analyses that are situation-specific, although the visible impact of those risks has begun to highlight the prominence of water in the manufacturing sector.

Section 3.3 of this report reviews water valuation methods and metrics as applied to various manufacturing subsectors at the facility level, such as the marginal value of water, water average productivity, the shadow price of water, the price elasticity of water demand, and the output elasticity of water demand. It also presents water valuation metrics used at the regional or economy-wide level that were established to investigate barriers to sustainable water supply and use and the associated economic growth in particular regions and economies. Next, Section 3.4 summarizes several case studies of water valuation from multinational manufacturing corporations. The report authors show that better data transparency has led some large manufacturers to champion water sustainability via supply chain sustainability initiatives, environmental profit-and-loss accounting, estimating risk-adjusted values of water, hydro-economic modeling, natural capital asset valuation, and developing value chain indices. This section demonstrates that true cost accounting and internalizing the externalities of the social and environmental costs of production would result in more efficient use of water as a scarce natural resource and improve manufacturing sector sustainability.

As described above, the throughline of this report is water stress exacerbated by climate change, data gaps, and undervaluation, resulting in challenges to achieving water supply sustainability and resilience. One of the report's major contributions is highlighting research and development needs for technology innovation and the potential for advanced analyses to illuminate productive paths forward. After providing an introduction to the topic, Section 4 provides various exemplars of engineering, technologies, and analyses that support resilience strategies.

Section 4.2 summarizes water resilience enhancement strategies that aim to minimize the negative effects of water-related outages on the volume, pressure, quality, or other essential aspects of water. These strategies are designed to reduce both the exposure to such outages and the time required for recovery. Implementing these measures can safeguard manufacturing operations and the watershed's overall health against adverse consequences. To reduce water usage and increase efficiency in manufacturing operations, various measures can be adopted, including conserving water through heat exchanger networks to reduce boiler feedwater demand, servicing and retrofitting cooling systems, and exploring alternative water sources like gray water. Manufacturing unit processes can be modified to consume less or no water, for example, by using gas-based technologies (e.g., carbon dioxide-based coolants and cleaning solutions, laser ablation, etc.) to provide heat and mass transfer, dissolution, or other functions typically served by water. In addition, water reuse can be incentivized by treating and utilizing gray water for non-production purposes, either through separate water systems or a combination of potable and recycled water sources. Moreover, enhancing the robustness of the water supply involves diversifying water sources, implementing multiple inlet pipes, and maintaining water storage and distribution infrastructure. Overall, companies should conduct life cycle assessments to reduce the water footprint of manufacturing and mitigate water-related risks in supply chains.

Section 4.3 discusses how accounting for the true cost of water can help identify cost-intensive operations and make water efficiency measures more economically attractive. Accurate metering and submetering of water use, intakes, and discharge helps facilities understand their water use and better plan resource optimization efforts. For example, by applying the DOE Plant Water Profiler tool within the manufacturing plant, facilities can disaggregate water use/consumption and true cost by manufacturing subsystems and processes. Findings in Section 4.3 from three manufacturing plants (iron and steel, fiberglass, and vinyl siding) reveal that assessing the true cost of water shows that a large share of this cost can be associated with expenditures not associated with purchasing water, such as water pumping energy and wastewater treatment costs. At these three plants, the true cost of water was 1.3–3.2 times the acquisition price. Measuring all the costs related to water use identifies cost-intensive operations, enabling the optimization of water use while yielding significant financial returns for manufacturers. This section also demonstrates that a more detailed understanding of water flows and quality requirements can lead to less consumptive water use in manufacturing via water efficiency and substitution.

Next, a case study (Section 4.4.1.1) on employing "dry factories" technologies shows how introducing water-less or water-lean technologies to water-intensive processes can dramatically reduce on-site water use while offering other occupational health and environmental benefits. As an example of a "dry" or water-less technology, this section compares the life cycle impacts of gas-based metalworking fluids with water-based metalworking fluids based on their functional performance reported in the literature. Gas-based metalworking fluids show significantly improved tool life (between 2–100 times) but have a higher life cycle primary energy and water use than water-based fluids.

Thus, the overall impacts of these novel technologies must be assessed from a life cycle perspective (i.e., tradeoffs could include higher energy and emissions, toxicity of alternative fluids, and water impacts throughout the supply chain of alternative fluids). Life-cycle energy and water use of gas-based substitutes for water-intensive industrial processes can be reduced through optimization and/or targeted delivery of gasses when used in an open loop and through closed-loop operation of the gas whenever technically feasible. When used judiciously, gas-based technologies can not only dramatically reduce on-site water use, but may potentially provide other environmental and occupational health benefits. Researchers and policymakers must consider whether such technologies are likely to see high adoption across the industry and whether such adoption may lead to adverse social or environmental rebound effects.

Next, Section 4.4.1.2 evaluates the potential for on-site water reuse opportunities by presenting a theoretical framework that compares the energy required for the single use of water with that for reuse. The analysis establishes that based on available data, key subsectors, such as primary metals and petroleum and coal products, are already treating much of their wastewater to a standard sufficient for on-site reuse. One key research and development opportunity relates to improving the treatment of total suspended solids, which would allow for more on-site water reuse. The section concludes that better data to illuminate the relationship between energy and water in the context of on-site manufacturing water reuse would allow manufacturers to improve resilience and lessen their footprint on local watersheds.

Section 4.4.2.1 then showcases a newly developed framework (for outside the plant) to determine an optimal manufacturing water supply portfolio that balances resilience in water supply options and embedded greenhouse gas emissions for a given region. The method includes understanding regional manufacturing water withdrawals, hydrological conditions, and energy requirements, and the GHG emissions associated with procuring and treating water via sources such as municipal, surface, and groundwater supply. The optimization framework outlines multiple scenarios focused on baseline energy usage, lowest energy consumption, and county or facility resilience (based on restricting water withdrawals from a single source below certain thresholds). The authors illustrate this method by applying it to a Louisiana parish. In examining the tradeoffs between a diverse water supply portfolio and the decarbonization of water supplies, the analysis suggests that in this particular parish, water supply resilience comes at the expense of energy use.

Finally, Section 4.4.2.2 performs an exploratory analysis to determine how much of U.S.

manufacturing wastewater could be cost-effectively treated with curtailed electricity arising from increased renewables penetration. The authors propose that better coordination between the electric power and water sectors through load shifting via flexible wastewater treatment scheduling can yield as yet unrealized economic opportunities. The authors' supplemental analysis to a recent paper estimating the impact of paying generators for curtailed electricity demonstrates that a payment of $30/megawatt-hour (MWh) (roughly half the cost of electricity of average industrial users) would supply enough curtailed electricity to meet water reuse treatment for U.S. manufacturing discharges. However, such flexible systems would also require certain additional expenditures to enable flexibility. Further, appropriately quantifying the scale of this economic opportunity would first require addressing several institutional and operational concerns via additional research and development.

Ultimately, this report emphasizes that water stress for manufacturers is exacerbated by our rapidly changing climate, increased competition for limited water supplies, and water undervaluation. The dearth of data describing who, when, where, and how water is used for manufacturing—as well as water quantity, quality, and source—inhibits informed water management and decision-making. Additionally, though not addressed in this report but critical to consider, the environmental justice implications of manufacturing water withdrawals may become more pronounced as water allotments—either officially by a water authority or as perceived by a community—take shape in response to growing water scarcity. Future research, analysis, and action should be framed through the lens of these two intertwined issues. However, without additional data, research, and technology development, water stress and associated risks are likely to result in cascading and increasingly severe consequences for the manufacturing sector and stakeholders of all kinds in surrounding watersheds.

1. Introduction

Section 1 Summary

- Water and manufacturing are inextricably linked, impacting the day-to-day critical operations of a manufacturing facility and the broader watershed and water infrastructure of which the facility is a part.
- Manufacturing industries use water for critical functions, including processing, cooling, cleaning, mass transport, dissolution/precipitation, irrigation, and fire suppression.
- Despite water's criticality, its use and discharge characteristics in manufacturing are poorly tracked and understood, leaving facilities vulnerable to natural and human-caused water-related hazards.
- Some firms do, however, attempt to assess and mitigate various aspects of their water criticality and risk. Their assessments rely on surveys and past exposures to disruptions, and mitigation measures range from setting water conservation goals to factoring into business decisions a price of water much higher than their cost to procure it.
- Key research questions aimed at increasing manufacturing resilience and lessening the impacts of manufacturing water use on watersheds are articulated.
- Elements of Section 1 draw on the following work published by report authors: Rao et al*.* (2017) and McCall et al*.* (2021).

1.1 Objectives of This Report

Broadly, this report aims to help manufacturers become more resilient to water risks by fostering an improved understanding of manufacturing water use and informing priority areas for developing water-related technologies. The authors define *manufacturing* as industries encompassing North American Industry Classification System (NAICS) codes 31–33,[1] which excludes mining, agriculture, construction, and utility-scale power plants. Better insights into manufacturing water use will enable the identification of systemic improvements at the intersection of water, energy, and risks in the manufacturing context. This report is intended for a wide audience, including manufacturers, decision-makers, researchers, and policymakers.

U.S. manufacturing water use characteristics are generally poorly understood. One objective of this report is to establish the current state of understanding of manufacturing water use characteristics. In so doing, it will illuminate how more representative and precise estimates of manufacturing water use, discharge, and consumption, as well as a more comprehensive understanding of the economic value of water, are necessary for accurate and actionable technology assessments and evaluation. Another objective is to highlight advanced

[1] Federal statistical agencies use NAICS to uniformly classify business establishments when collecting, analyzing, and publishing statistical data related to the U.S. business economy; see https://www.census.gov/naics/.

opportunities for water conservation to support resilience. Fostering resilience through better data and management of water-related risks will yield a variety of benefits for manufacturers and other watershed users.

To meet these objectives, this report is structured as follows. This first section describes the general context of manufacturing water use and posits that risk is the driving concern for water conservation in the manufacturing sector. It also defines resilience in the context of water risks and summarizes current resilience strategies undertaken by U.S. manufacturers. Section 2 focuses on the estimates of water use, in terms of intake and discharge, necessary for comprehensive analyses of water risk. It surveys existing data and methods to summarize current data availability, presents results from advanced regression estimation methods, outlines two exemplars of risk analysis concerning sectors at physical and thermal risk, and underscores the role of technology innovation in addressing facility-level data collection difficulties. Section 3 argues that a risk-informed, more comprehensive economic valuation of water is key for guiding and informing technology development and deployment. Section 4 presents a selection of technologies, engineering advances, and operational responses that could support water resilience strategies. Finally, Section 5 summarizes the key conclusions of the report and guidance for future work.

1.2 Background

Water is a ubiquitous and essential input for industrial operations. The United States is one of the largest users worldwide of industrial water,[2] withdrawing 151.8 billion gallons per day (BGD) (FAO 2021). The use of manufacturing water represents about 6% of total national water use (Rao et al. 2017). Manufacturing water use varies by subsector, as different activities require different inputs of water. In fact, industrial operations require a sustained supply of water in the right quantity, of the right quality, at the right place, at the right time, and at the right price (UNESCO 2012). Yet, despite the complexity of water needs for industry and the importance of assuring the continued operation of the industrial sector for socio-economic development, in the U.S., industrial water use is not consistently measured, disclosed, or reported. In fact, there exist no consistent national datasets of total manufacturing water use by economic sector over time and across geographical regions (Blackhurst, Hendrickson, and Vidal 2010; Gleick 2016; Josset et al. 2019; Marston et al. 2018; Ruddell 2018; McCall et al. 2021; Marston et al. 2022).

Water is an essential resource used by all manufacturing industries for several purposes, such as processing (e.g., washing/rinsing, steam generation, process cooling), as a raw material, for ancillary processes (e.g., emissions abatement, fire suppression), to serve domestic uses (e.g., bathroom), and for irrigation. To utilize water, an individual manufacturing facility interacts with the environment and watershed as illustrated in Figure 1.1. Flows 1 and 2 depict withdrawals from municipal water systems and surface waters, respectively, while Flow 3 represents water withdrawals from groundwater and rainwater. Water from these varied sources may be treated

[2] Here, the Food and Agriculture Organization of the United Nations (FAO) distinguishes industrial from municipal and agricultural water withdrawals. Generally, this report uses the term *industry* when it is in accordance with the term used in the cited work; *industry* typically includes manufacturing as well as other subsectors depending on the data source. When this report uses the term *manufacturing*, report authors are specifically referring to the subsectors encompassing NAICS codes 31–33.

onsite at the industrial facility prior to use in manufacturing processes, cooling systems, and ancillary services (Flow 4). After use and before discharge (Flow 6), the discharge may undergo on-site wastewater treatment (Flow 7) or be discharged directly to a receiving water body (Flow 9) or a municipal wastewater treatment facility (Flow 10). Discharges treated on-site may be discharged back into the watershed directly (Flow 8), reused in the facility (Flow 5; note that some reuse opportunities will not require any treatment first and can be cycled internally through processes), or sent externally to a municipal treatment plant. Finally, Flows 11 and 12 represent water encapsulated in industrial products or lost from the watershed through evaporation and other losses, respectively.

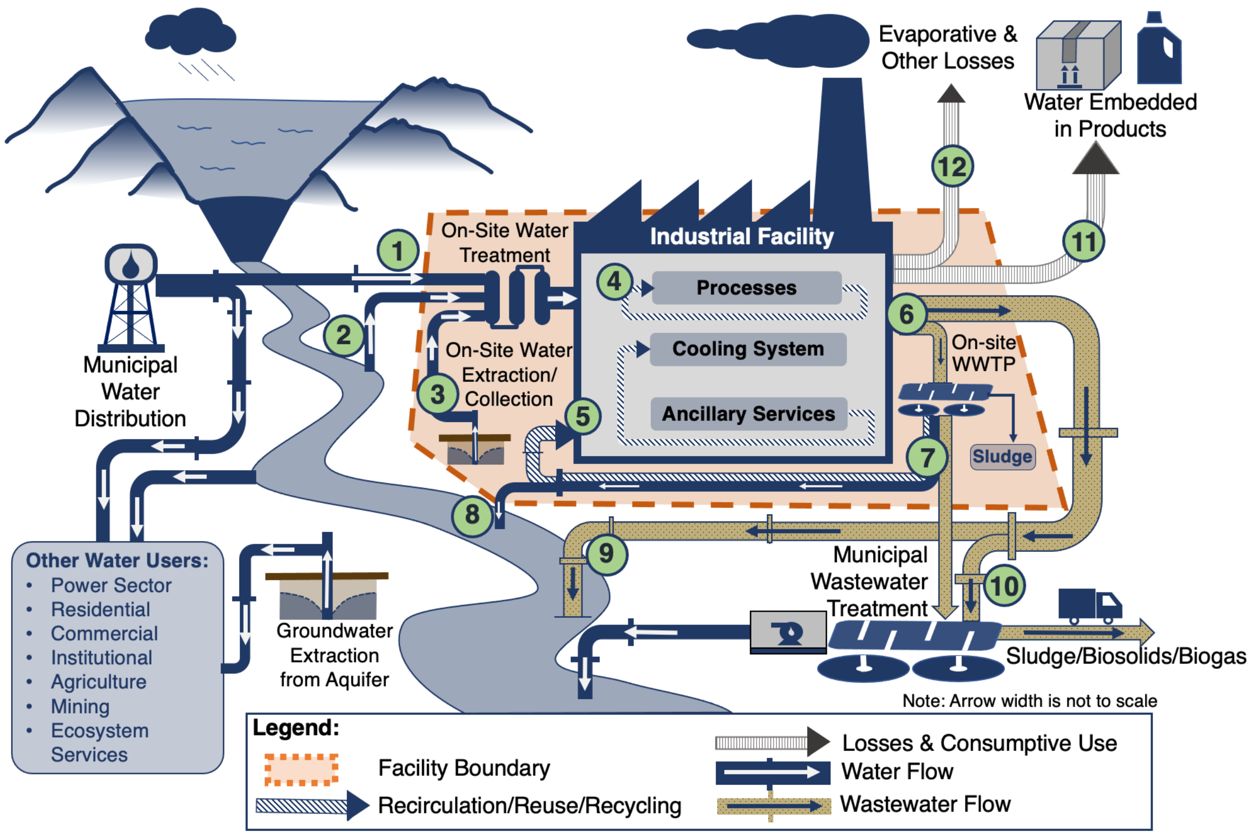

Figure 1.1 Schematic of manufacturing facilities' interaction with the watershed and environment

Against this backdrop, the current and future ramifications of interactions between the manufacturing facility and watersheds can be better understood. Excessive and rapid water resource exploitation, beyond the recovery rate of ecological systems, can lead to harmful consequences that span geographical regions and economic sectors. Economic development and water availability have had a reciprocal relationship; while economic forces have driven industrial water use,[3] lack of water availability can hinder development (Hoekstra 2014,

[3] This report distinguishes between water use and water consumption as follows in order to use consistent terminology (Grubert et al. 2020). *Water use* refers to the total amount of water withdrawn from a source to be used and is often related to the level of demand. In contrast, *water consumption* refers to the share of water use that is not returned to the original water source post-withdrawal. Water

UNESCO 2012). With increasing water demands, industries may find they compete for limited resources with other water users. In addition, hydro-climatic variability can intensify the uncertainty of sustained water supply and reveal systemic risks.

Figure 1.1 also shows the linkages between a manufacturing plant and its watershed, which is subject to physical risks. In a rapidly changing world, manufacturers may no longer be able to rely on the availability of the necessary quality and quantity of water when required. Water supplies that manufacturers depend on are directly threatened by climate change, population shifts, and continued urbanization and industrialization, which lead to or intensify droughts and eutrophication.

Concerning drought, Figure 1.2 displays the average change in drought conditions for the last 120 years for the contiguous U.S., with an overall national trend toward wetter conditions—but significant and consistent drier conditions in the West. Looking ahead, Strzepek et al. (2010) predict "very substantial and almost universally experienced increases in drought risk" by 2050 across most of the U.S., with both the incidence of and uncertainty associated with drought strongly correlated with higher greenhouse gas emissions scenarios. Similarly, Overpeck and Udall (2020) foresee emissions-driven aridification and decadal to multidecadal droughts in western North America—with "dire" implications for water security and ecosystems—as well as more acute arid events becoming part of "the new normal" in other parts of the continent. In addition to the lack of water, climate change will jeopardize water quality in concert with other drivers under human control. These include excessive agricultural nutrient runoff, resulting in more frequent, severe, and widespread occurrences of toxic algal blooms, severe hypoxia, and microbial outbreaks—all of which impair the water quality to sub-usable levels (Michalak 2016).

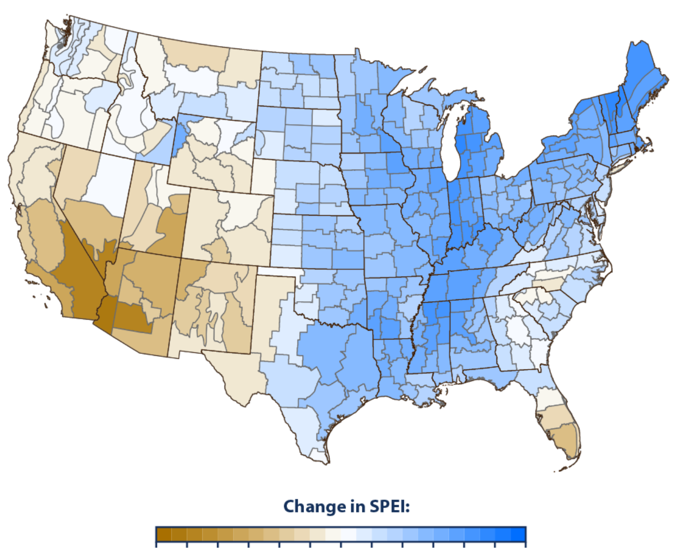

Figure 1.2 Total change in drought conditions from 1900–2020 for contiguous 48 states
Based on the long-term average rate of change in five-year Standardized Precipitation Evapotranspiration Index, where brown areas represent decreased moisture and blue areas represent wetter conditions.
Figure source: EPA (2021)

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consumption can encompass water lost to the atmosphere or incorporated into an industrial product; thus, this water is not available for reuse by the facility or any other water user within the watershed.

U.S. manufacturing is threatened not only by these primary risks to water supplies but also by secondary risks such as flooding from increased precipitation, sea level rise, and intensified hurricanes and storm surges, as well as supply chain vulnerabilities related to water (Bureau of Transportation Statistics 2022, Horowitz 2022, Hui 2022). Climate change is driving extreme precipitation events, which have the potential to flood manufacturing plants and curtail operations. Wing et al. (2018) project the value of exposed assets by U.S. states within the 100-year floodplain under various emissions scenarios, finding substantially higher exposure than estimated by the Federal Emergency Management Agency (FEMA) in urban centers on the shores of the Great Lakes, along the Pacific Coast, and across the inland western half of the country. Wobus et al. (2017) model the difference in inland flood damages for lower and higher emissions pathways as nearly $4B annually by 2100. Furthermore, Rhoades et al. (2021) estimate that annual mean flood damages from atmospheric rivers that make landfall in the western U.S. will increase by around $1B for every Celsius degree of additional warming relative to today. Figure 1.3 shows anticipated increases in the average annual loss by county from Wing et al. (2022), who incorporate new information from inundation modeling to show a 24.1%–29.1% increase in flood risk in the United States by 2050 solely due to climate change under the intermediate Representative Concentration Pathway (RCP), RCP 4.5.[4]

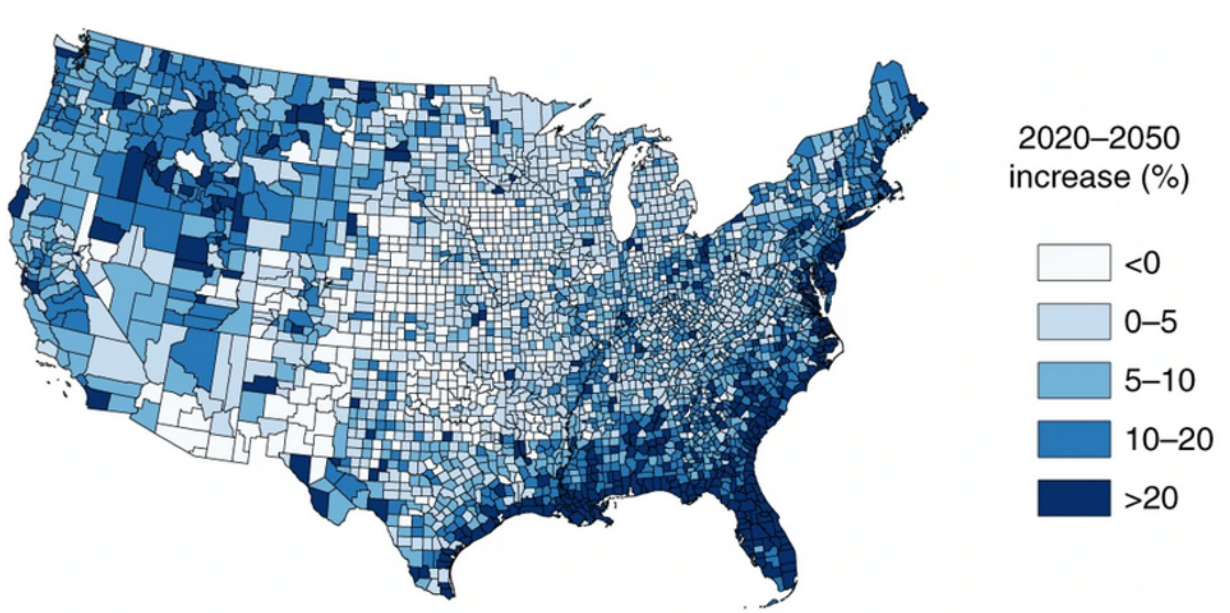

Figure 1.3 Relative increase in average annual loss from future U.S. flood risk by county
Excerpted from a larger figure by Wing et al. (2022)

In addition to significant changes to precipitation and other flood risks arising mainly from the accelerating pace of climate change, human factors related to land use and water demand also

[4] A Representative Concentration Pathway (RCP) is a greenhouse gas concentration (not emissions) trajectory adopted by the Intergovernmental Panel on Climate Change (IPCC) for climate modeling and research. RCP 4.5 is one of four RCPs the IPCC selected and defined by their total radiative forcing (cumulative measure of human emissions of GHGs from all sources expressed in Watts per square meter) pathway and level by 2100. The RCPs were chosen to represent a broad range of climate outcomes, based on a literature review, and are neither forecasts nor policy recommendations. https://sedac.ciesin.columbia.edu/ddc/ar5_scenario_process/RCPs.html

affect freshwater availability. Figure 1.4 displays changes in terrestrial water storage (in groundwater aquifers and large river basins) detected over 14 years of data from the National Aeronautics and Space Administration (NASA)'s Gravity Recovery and Climate Experiment (GRACE) satellite mission. In the U.S., California and the southern Great Plains are two areas with reduced freshwater availability resulting from "possible or partial direct human impact," with major groundwater depletion from irrigated agriculture (in the Central Valley of California and the central and southern High Plains aquifer) compounded by droughts (Rodell et al. 2018). The wetter trend in the northern Great Plains stems from significant drought in 2001–2003, followed by nearly 11 years of higher than average precipitation, with flooding in 2010–2011. Patterns of land use and water demand will likely worsen the impact of precipitation changes in some of these regions. Human impacts and climate variation will continue to threaten water availability, intensifying under "business as usual" scenarios.

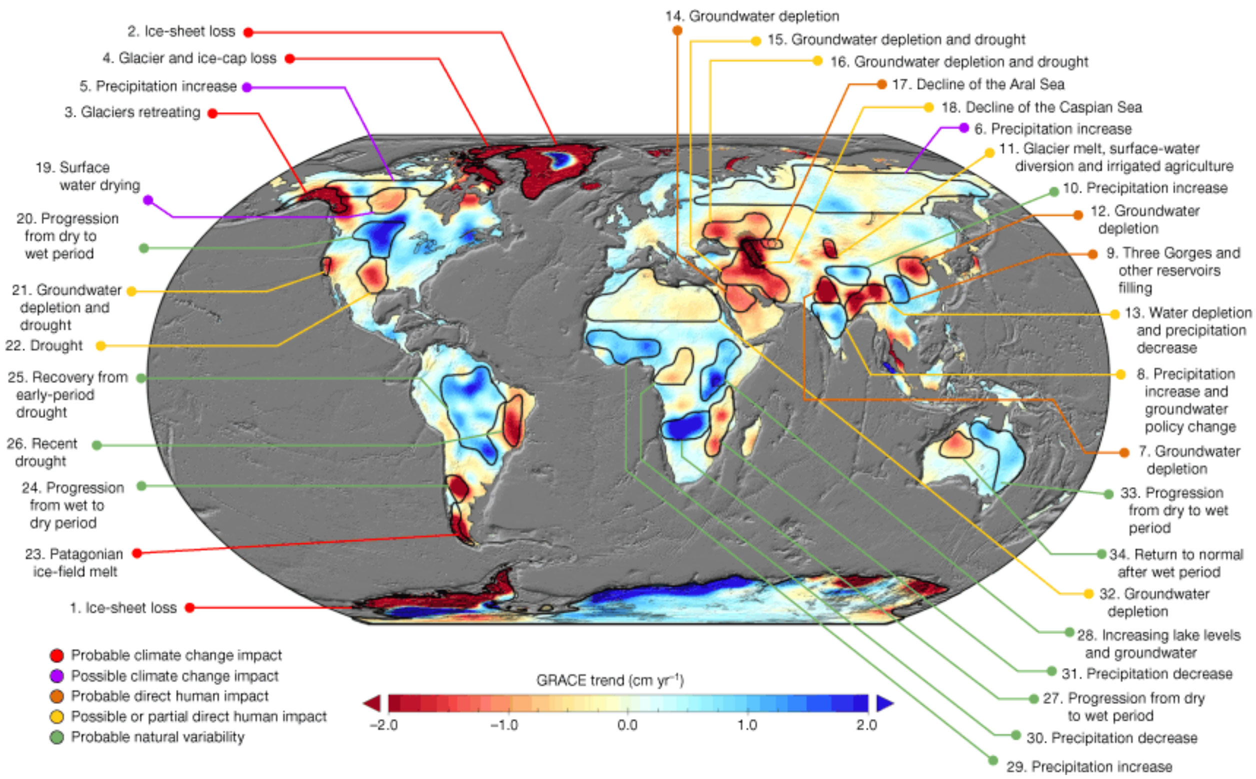

Figure 1.4 Trends in terrestrial water storage in centimeters per year from NASA's GRACE observations from April 2002 to March 2016

Figure source: Rodell et al. (2018)

Moreover, given the prevalence of global supply chains, U.S. manufacturers are often subject to indirect water-related risks along those chains; more than 90% of industries consume more water in the upstream supply chain than in direct operations (Marston et al. 2020). When a vulnerable sector is exposed to a significant hazard, the effects can propagate through the economy via supply-chain disruptions and price shocks (Sadoff et al. 2015). For example, a drought in Taiwan was a significant factor in the global semiconductor shortage in 2021 (Barbiroglio 2021), creating adverse downstream effects on the automotive industry and consumers in the U.S. (Leibovici and Dunn 2021). Similarly, shifting crop patterns and yields (Gold 2011; Chen et al. 2018; Marklein et al. 2020) will likely negatively affect manufacturers in subsectors that depend upon these crops or biofeedstocks, such as food, beverage, textile, and chemical manufacturing. At the other end of the spectrum, floods in the Midwest have affected agricultural fields that perturb the ethanol industry, consequently affecting gasoline prices and other industries that use ethanol as a feedstock (Reuters 2019).

The legal system of water rights is germane to understanding water-related risks for manufacturers. In general, two legal doctrines underpin water rights in the U.S., with the riparian doctrine typical for eastern states and the doctrine of prior appropriation dominant in the West. With its principle of beneficial use, the latter is likely to be a barrier for manufacturing facilities that reduce withdrawals because a water right is forfeited if it is not used (Burness and Quirk 1979). The seniority of water rights for manufacturers in the western states is also key: those with more senior water rights (i.e., acquired earlier) face less risk of losing access to water during shortages than more junior water rights holders. Certain states have passed laws to ameliorate the rights-related disincentives for conservation, reuse, and source substitution. In Arizona, loss of surface water rights is no longer at risk when using an alternative source or exchanging water. California has classified recycled water as a beneficial use to increase conservation and reuse. Instead of using water from an existing right, Oregon statutes allow water source substitution, such as reusing water and using reclaimed water. Washington promotes the specific reuse of agricultural industrial process water from food processing by amending its water rights system (Schempp 2010). However, in a system “akin to slapping a bunch of different state Band-Aids on the problem,” making prior appropriation more consistent with the realities of western water shortages requires better quantifying water availability and potentially reducing existing rights to achieve sustainability—as Australia has done (Schilling 2018).

In addition, future regulatory responses to these changes will likely affect manufacturers in currently unknown ways. Manufacturers may also experience reputational risks depending on how they manage interactions with watersheds and the associated public perception. Moreover, in the presence of deteriorating water quality and quantity conditions, risk (whether physical, reputational, or regulatory) can impact industrial operations in multiple ways. The determinants of the effects of risk are the type of hazard (such as slow-onset droughts, sudden floods, and chronic environmental degradation like salinization, hypoxia, and waterlogging), the degree of exposure, and the existing level of vulnerability.

The effects of risk can propagate across users not only through economic linkages but also by increasing competition for resources in a shared geographical location. U.S. metropolitan areas house a large portion of manufacturing facilities—driven by siting conditions favorable for industry (e.g., access to transport and labor), agglomeration, and co-location (Helper, Krueger, and Wial 2016)—that compete with residential and commercial water users. As water risks become more frequent and severe, ensuring water security and equitable water allocation for users will be increasingly important. Greater focus and further research on these risks will be needed to reduce their impact on manufacturers, the environment, and broader society.

1.3 Identifying Water Risk Mitigation Technologies and Practices

The water needs of manufacturing facilities and specific processes can vary considerably in quantity, quality, and cost, creating subsector-specific risks and offering unique improvement/mitigation opportunities. Industries such as food processing, pharmaceutical, and high-technology industries have high water-quality requirements for specific processes. In contrast, facility operations, such as water cooling or ancillary services, require lower intake water quality and can take advantage of water reuse, recycling, and reclamation. Moreover, the required treatment of industrial effluents to minimize the impacts on receiving water bodies can also vary significantly. For example, industries like tanneries and chemical manufacturing can potentially release toxic pollutants to local water bodies, although technology exists to effectively remove some of the known contaminants on-site before discharge. Industrial water uses and effluents also have distinctive characteristics and opportunities that set them apart from other economic sectors.

The complexity of the differences in water requirements among processes within a facility provides opportunities to increase water productivity and reduce costs by optimizing water use. Water management efforts, such as technological advances that improve water productivity in industrial processes, can help decouple water resource exploitation from economic development. However, financial motivations for water conservation are weak, largely because water is significantly undervalued in manufacturing. Financial planning has not incorporated watershed impacts and compliance issues because they remain unexamined in the manufacturing context, except in individual instances. Also, manufacturing water use is relatively small compared to agricultural and other sectors at the state and national level, so agencies have often ignored it. In fact, water conservation is a primary mechanism by which manufacturers can reduce the effects of physical, regulatory, and reputational risks and increase their resilience in the face of more uncertain water supplies.

To better understand the manufacturing sector's impact on watersheds and to determine opportunities for water technology research and development (R&D) and policy to enhance resilience, McCall et al. (2021) established four strategic high-level research questions. While this report only begins to answer these questions, the authors have identified them as critical for advancing the understanding of manufacturing water risk and resilience.

- (Q1) How do water withdrawals, discharges, and contaminants of concern from different manufacturing industries impact local watersheds and communities, and what quantitative metrics capture these impacts?
- (Q2) How do manufacturers use water within their facilities, relative to both quantity and quality requirements, and how does their use compare to the theoretical minimum amount of water needed to provide an economic service?
- (Q3) What process improvements (e.g., water reuse technologies, water efficiency improvements, and detailed sensor monitoring and controls) are available to manufacturers, and what R&D is needed to develop technologies to lessen the impacts of manufacturing water use on watersheds?
- (Q4) How do current and future manufacturing water use and industrial colocation impact regional planning processes, and how does changing water availability impact manufacturing operations and investment decisions?

(Q1) seeks to understand and limit the impact of manufacturing water use on watersheds and local environments. Without a detailed understanding of possible answers to this question, it is impossible to establish metrics for watershed impacts, risk severity, water efficiency, water-related emissions, resilience, and compliance costs for manufacturers. Exploring potential answers to (Q2) and (Q3) would support targeting water end uses with high potential for conservation and identifying needed improvements to encourage water recirculation, reuse, recycling, and efficiency measures within manufacturing plants. Water reuse and efficiency can reduce impacts on the local environment, but without understanding where to look for opportunities and the associated cost tradeoffs and other impacts, reuse and efficiency are unlikely to be adopted broadly across the manufacturing sector. Answers to (Q2) and (Q3) can facilitate the development of R&D targets for new technologies and processes, as well as water conservation goals for existing processes and equipment. Finally, (Q4) looks to existing and future impacts and potential competition with other sectors in a changing climactic and regulatory environment. With the increasing potential for drought and other precipitation changes, the manufacturing sector will compete with other uses of water, and the increasing competition might negatively impact manufacturing production, local economies, and the environment. Irrespective of competition from other sectors, changes to current manufacturing operations and practices may be required to adjust to new water availability conditions. Ensuring that up-to-date water metrics are available to regional planners and manufacturers will allow for better-informed decisions regarding local water use. Note that the paucity of data on manufacturing water use impedes meaningful progress in addressing all of these research questions.

This report seeks to elevate the importance of these research questions—and begins answering them—by focusing on manufacturing water risk and resilience, as well as the connections between a manufacturing facility and its watershed. Some sections draw upon other recently published papers by the authors, referencing them accordingly.

1.4 Water Resilience in Manufacturing

The concept of resilience encompasses different definitions, dimensions, and metrics. This section defines the working definition used throughout this report. The root of the word *resilience* is *resilio*, meaning to spring or leap back. One should not conflate resilience with *reliability,* which in the resource (e.g., water, energy) context, can be defined as the ability of a system to supply the resource in the quantity, with the quality, and at the time needed by users. Additionally, this report primarily focuses on "hard" resilience (e.g., technological redundancy). While resilience has multiple dimensions beyond this report's working definition that deserve further attention, including "soft" resilience (e.g., adaptive management strategies, "safe-to-fail" approaches, and minimizing bounce-back time for system functionality), these are outside the scope of this report.

1.4.1 Definition of Resilience

Although since the 1970s, resilience has been defined and studied in several fields (e.g., ecology, social science, economy, and computing), researchers have only recently applied this concept in safety engineering and risk management studies. When considering an infrastructure system (i.e., manufacturing facility or asset), the definition of resilience varies considerably depending on the level of analysis (i.e., asset, facility, system, or system of systems). This section presents definitions of resilience, risk, and supporting terms used in this report. Further, it examines actions that help strengthen the resilience of manufacturing systems to water loss and other water-related disruptions.

Among all existing definitions, those proposed by the U.S. Department of Homeland Security (DHS) and the United Nations Office for Disaster Risk Reduction (UNDRR) represent a solid synthesis of the distinct abilities generally identified to enhance resilience to disruptions.

The UNDRR defines *resilience* as "the ability of a system, community or society exposed to hazards to resist, absorb, accommodate, adapt to, transform and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions through risk management" (UNDRR 2017).

The DHS defines *resilience* as "the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions. Resilience includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents" (The White House 2013).

These two definitions highlight connections between the core capabilities contributing to resilience and the four phases of emergency management and recovery from operational disruptions: preparedness, mitigation, response, and recovery. Figure 1.5 illustrates the relationship between the different components of resilience and the occurrence of a disruptive or adverse event. The red line represents the level of performance of a given activity (e.g., production in the case of a manufacturing plant) over time. After a disruptive event in a system occurs, its performance declines. The system's resilience determines both the magnitude of the decline and the amount of time required to return to its pre-event equilibrium (or some other new equilibrium).

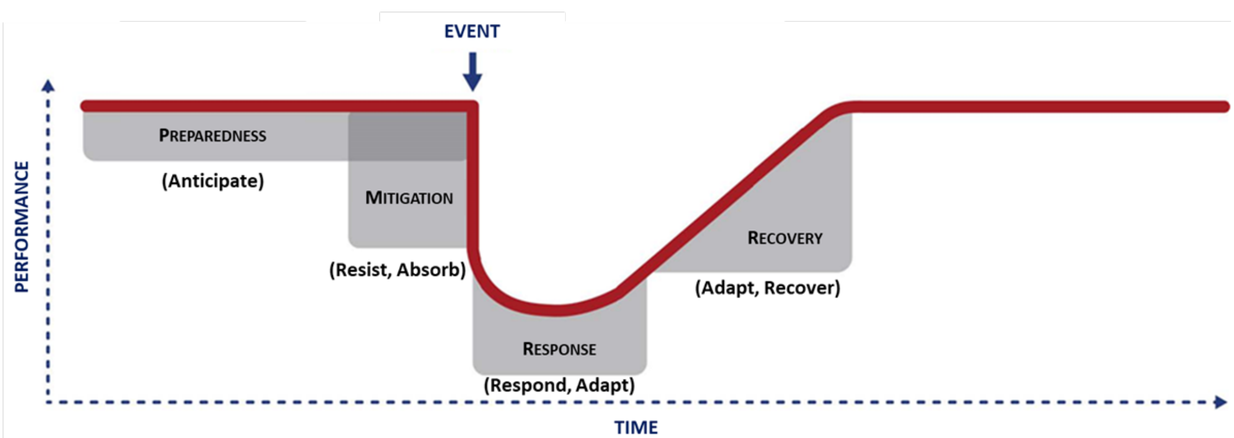

Figure 1.5 Components of resilience and the timing of an adverse event
Figure adapted from Carlson et al. (2012)

The DHS Risk Lexicon defines *risk* as "the potential for an unwanted outcome resulting from an incident, event, or occurrence, as determined by its likelihood and the associated consequences" (DHS 2010, 27). *Risk* is thus traditionally defined as a function of three elements: the threats to which an asset is susceptible, the vulnerabilities of the asset to the threat, and the consequences potentially generated by the degradation of the asset.

The DHS Risk Lexicon further defines *threat* as a “natural or man-made occurrence, individual, entity, or action that has or indicates the potential to harm life, information, operations, the environment, and/or property” (DHS 2010, 36). Sometimes, the term *hazard,* which is a “natural or man-made source or cause of harm or difficulty,” is used instead of threat. However, as the lexicon explains, a “hazard differs from a threat in that a threat is directed at an entity, asset, system, network, or geographic area, while a hazard is not directed” (DHS 2010, 17). *Vulnerability* is a “physical feature or operational attribute that renders an entity open to exploitation or susceptible to a given hazard” (DHS 2010, 38). *Consequences* are the “effects of an event, incident, or occurrence” (DHS 2010, 10).

A challenging yet critical question concerns where and how resilience fits into risk determination, since understanding this link is vital to developing sound risk and resilience assessment methods. As identified in national policies, such as the 2013 National Infrastructure Protection Plan (DHS 2013), *risk management* includes resilience and promotes an all-hazards approach that integrates human-caused threats and natural hazards. Risk management and resilience management strategies are inseparable and complementary. Organizations implement risk management strategies to mitigate known threats; they implement resilience management strategies in case the protection measures are insufficient to prevent negative consequences from known or unknown threats. Resilience management strategies can, therefore, improve the flexibility and adaptability of manufacturing and infrastructure systems by allowing hazard-affected systems to operate at an acceptable level of performance. In addition to their potential direct effect on manufacturing operations, four types of hazards described in the next section may also indirectly affect the manufacturing sector through its supply chains.

1.4.2 Water-Related Hazards and Vulnerabilities in the Manufacturing Sector

The manufacturing sector is a main contributor to the gross domestic product and national employment rate. The disruption of this sector could lead to significant economic impact. A hazard is anything that can disrupt or impact manufacturing and its supply chain operations. Some are universal, while others (e.g., natural disasters, drought, regulations, aging infrastructure) vary by geographic location. Hazards commonly take advantage of or affect a system because of specific vulnerabilities or points of weakness. The manufacturing sector is subject to four main types of hazards: (1) natural hazards, (2) technological accidents, (3) human-caused threats, and (4) pandemics. These hazards can affect manufacturing operations by being present at the manufacturing site or impacting the supply chains serving the site.

1.4.2.1 Natural Hazards

Natural hazards include not only natural disasters and extreme weather events that impact entire regions but also smaller weather events that may significantly impact manufacturing operations, upstream and downstream suppliers and customers, and other dependent sectors. Reed et al*.* (2022) discuss the emerging science of multi-sector dynamics, which explores the propagation mechanisms, consequences, and mitigation strategies for the impacts of earth systems on human systems and vice versa at a broad level, with a focus on critical goods, services, and amenities delivered to people. In this section, the report briefly discusses some natural hazards in the context of manufacturing.

Manufacturing sector assets are vulnerable to several types of natural hazards such as droughts, floods, wildfires, tornadoes, hurricanes, high winds, and heavy snow. Impacts from natural hazards can be direct when a given factory is in the zone of influence of the hazard, or indirect when the natural hazards trigger cascading failures of supply chains and lifeline sectors (i.e., communications, energy, water systems, and transportation systems) that may ultimately disrupt manufacturing operations. For instance, the recent floods in the western U.S. driven by amplified atmospheric rivers due to climate change (Michaelis et al. 2022) disrupted operations in the food and beverage industry in California, affecting food availability and prices country-wide (Lee 2023). Natural hazards likely to impact the manufacturing sector also vary by the location of the manufacturing asset and the types of manufacturing processes.

Droughts and Floods

The most obvious natural hazards impacting water use in manufacturing are droughts and floods, as they can affect the availability and quality of water and disrupt production systems. Drought and flooding may directly impact manufacturing by affecting the availability and quality of raw water required for their operations.

Droughts lead to a decrease in water levels of both surface water bodies and aquifers and can ultimately create water scarcity. In addition, extended droughts can disrupt upstream supply chains for subsectors such as food and textile manufacturing. Droughts also critically affect the quality of raw water. For example, the combination of high temperatures and decreasing water levels can enhance algal production and bacteria concentration, as well as lower dissolved oxygen levels. The level of nutrients and water turbidity can increase in lake systems and decrease in rivers (Mosley 2015). Droughts may also affect the dilution of pollutants in water systems; in addition, intensified groundwater extraction during a drought can increase saline water intrusion, shift contamination plumes, expose deep aquifers to contamination, and cause land subsidence, which could impact the integrity of water conveyance infrastructure. Further, drought often leads to increased wildfire activity and extent, contaminating runoff from burned areas with ash and sediment.

Similarly, during a flood, the water’s physicochemical characteristics can change. Most directly, industrial waste containment systems are vulnerable to flooding that results in accidental release of contaminants. For surface water bodies, in addition to the potential increase of contaminants, flooding results in increased floating debris, which requires additional mechanical treatment and may cause equipment failure. In cases of both flooding and drought, damage to critical water supply or wastewater infrastructure can occur and affect the availability or quality of water.

In addition to affecting the availability and quality of water resources, floods and droughts generate significant economic, environmental, social, and health and safety impacts (Rosenbaum and Boulware 2006; Sarmiento and Miller 2006; National Drought Mitigation Center 2020). Although floods can be of different types (e.g., flash floods, river floods, and coastal floods) (USGS 2022; Zurich Insurance Company 2022), they usually lead to structural damages resulting from infiltrations, water stagnation, or physical forces applied directly to building structures (Marvi 2020). The debris, rocks, and mud carried downstream during flooding events can cause additional material damage to buildings and equipment. In contrast, direct damages from droughts are less instantaneous than those caused by floods. These drought damages usually occur over time and affect both underground infrastructure (e.g., pipelines, utilities' equipment, or building foundations) and aboveground infrastructure (e.g., roads) via soils shrinking during dry periods and expansion during wet periods (Schwab 2013). In addition, droughts can lead to reduced production from limited water availability, higher prices for agricultural inputs due to reduced yields and crop failure, and effects related to effluent quality regulations relative to a smaller volume of receiving waters.

1.4.2.2 Technological or Accidental Hazards

Technological or accidental hazards are industrial incidents resulting from dangerous procedures and infrastructure failures. Manufacturing procedures can potentially, by themselves, generate industrial pollution, toxic waste, factory explosions, fires, and chemical spills. Technological hazards may arise from a technical issue or human error but can also result from a natural hazard event. With respect to water usage, technological hazards have unique consequences. For example, an equipment failure can cause a water leak, potentially decreasing water volume and pressure. Depending on the magnitude and location of the leak, it can flood other equipment.

Another type of technological hazard can generate more severe consequences. Indeed, manufacturing operations may require using large quantities of chemicals for treating raw and sewage water that, if mishandled, may cause an explosion or emit chemicals and/or release contaminated water into the environment. Gabriel (2014) analyzes an industrial accident that adversely impacted nearby streams and drinking water supplies: after approximately 5,000 gallons of a chemical used in coal processing leaked from a storage tank into the Elk River, 300,000 residents in and near Charleston, W.Va. lacked access to drinking water for several days. In an incident related to transporting manufacturing inputs, a freight train carrying more than 700,000 pounds of vinyl chloride derailed in East Palestine, Ohio, leading emergency responders to incinerate the site and evacuate more than 1,500 residents (Tabuchi 2023).

1.4.2.3 Human-Caused Threats

Human-caused threats result from the intent and capability of an adversary to harm life, information, operations, the environment and/or property. Due to its economic, strategic, and iconic value, the manufacturing sector is an appealing target for deliberate attacks and terrorism. In addition to potential physical attacks, the sector is vulnerable to cyber-attacks that would disrupt industrial control systems, damage equipment, or steal corporate information and processes. In a recent example, an individual tried to poison a Florida town by hacking into the town's water treatment plant and tampering with the chemical additives used to treat the water (Greenberg 2021). When considering water usage in manufacturing, a human-caused threat could produce consequences similar to a technological hazard.

1.4.2.4 Pandemic or Infectious Diseases

Pandemic or infectious diseases can dramatically increase morbidity and mortality rates over a wide geographical area and cause significant economic, social, and political disruptions by decreasing the availability of staff and key personnel. The most recent and severe example is the COVID-19 pandemic, which lasted over 3 years. Water and wastewater utilities suffered declines in revenue and workforce, delays in critical capital projects, disruptions in the supply chains of crucial material inputs, and other factors affecting utilities' ability to provide clean and safe drinking water and wastewater/stormwater management (Butler et al. 2020). Further, without adequate water management plans, extended facility closures can cause water stagnation and increase the risk of microbial and heavy metals contamination in building plumbing systems (Proctor et al. 2020; Salehi et al. 2021). Contaminated water is known to be a major vector for the spread of infectious diseases. Likewise, microorganisms, such as bacteria naturally present in freshwater environments, can become a health concern when they grow and spread in industrial equipment such as cooling towers, hot water tanks and heaters, or large plumbing systems.

1.4.3 Current Resilience Strategies

Manufacturing industries may have alternate sources of water or water storage catchments to support some operations for short-term service interruptions. However, a long-term outage could cause a significant shutdown. For example, manufacturing industries rely on sanitary removal services to collect and treat sewage before releasing the water into the environment. Although alternatives can address short-term disruptions of these services, long-term disruptions would require ceasing manufacturing operations. Resilience enhancement measures can help reduce the negative consequences that could potentially result from existing hazards and infrastructure dependencies.

Reporting on corporate initiatives and strategies employed by manufacturers reveals current thinking and practices for realizing water resilience. Based on findings from voluntary water reporting in the Carbon Disclosure Project (CDP) database, members from all industries recognized water risk. However, the innovation and investment needed to reduce water risk often compete with other risk reduction and resilience measures (e.g., energy, cyber security, physical infrastructure) (CDP n.d.). This competition likely reflects the low cost of water (<1% of total expenditures), making water upgrades less economical than others, given the lower returns on investment and/or longer payback periods. Water risks identified by respondents included physical (e.g., scarcity), regulatory, reputational, natural disasters, and water quality concerns. Often, manufacturers reported their own facility operations had low water risk but their suppliers had high risks, which was outside the scope of CDP reporting. This indicates that manufacturers often pass off risk upstream in their supply chain and pay for that risk reduction in the price of products.

According to the CDP data, upgrades for water resilience occurred in response to extreme conditions and physical water risks, such as flooding and hurricanes. Some non-physical resilience strategies included increasing internal water reuse and identifying alternative water resources. However, manufacturers often implement these measures at a plant-level or regional basis (i.e., not company-wide). Some high-level strategies the CDP found included monitoring and measuring water volumes, setting water reduction and efficiency goals, tying water goals to corporate sustainability measures and C-level executive reporting and bonuses, and performing a watershed risk analysis to identify plants and areas of concern.

CDP water reports summarize responses to various voluntary questions designed to ascertain companies' risk identification and risk mitigation measures regarding water (CDP 2018). Companies use several methods to assess their risk. One method applies U.S. Securities and

Exchange Commission principles to establish risk as anything that impacts more than 5% of annual revenue or that investors raise as a concern. Another method employs the International Standards Organization (ISO) 31000 Risk Management Standard; see Figure 1.6. Finally, companies implement industry-standard tools, such as the World Resources Institute (WRI) Aqueduct tool or the World Business Council for Sustainable Development (WBCSD) Global Water tool,[5] to determine the plants and manufacturing operations located within water-stressed areas.

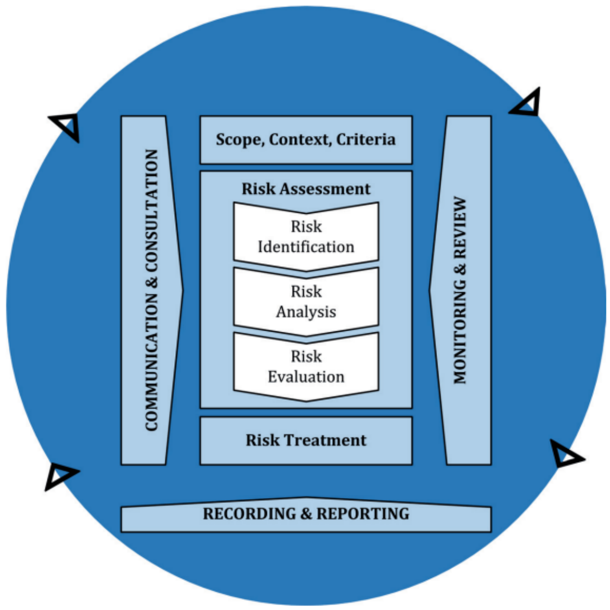

Figure 1.6 ISO 31000 reporting process

Source: A portion of Figure 1 in ISO (2018)

An overarching risk identified through screening random CDP water reports was that failure to report environmental risks and factors raised reputational and investor-driven concerns. These concerns could lead to periodic severe scarcity and shutdowns, and loss of the "license to operate" within the local community—meaning the community could rally support and influence local leaders to pressure a facility to reduce or completely stop their water withdrawals.

The authors examined CDP reports for 13 companies representing multiple manufacturing subsectors, including food, paper, chemical/pharmaceutical, aluminum, steel, power electronics, aircraft, pumps and compressors, and medical equipment manufacturing. While the study focused primarily on large multinational corporations, it also included a few smaller-scale manufacturers to provide varied perspectives. Table 1.1 summarizes the review findings to illustrate how companies assess and mitigate water risk; it is not a comprehensive review of company reports. The CDP established the metrics in Table 1.1.

[5] The WRI Aqueduct tool is available at https://www.wri.org/aqueduct, and the WBCSD Global Water tool at https://www.wbcsd.org/Imperatives/Nature-Action/Water-Stewardship/News/WBCSD-Releases-Updated-Global-Water-Tool-for-Sustainable-Water-Management.

Table 1.1 Examples of How Companies Assess and Mitigate Various Aspects of Water Risk

Metric	Findings
Importance of water	Some respondents expressed concern about access to clean water. In contrast, others explained that water did not impact their direct operations because they used very little water or the location was not water-stressed. A common theme in reporting reveals that manufacturers do not account for water risks passed off to upstream suppliers. Some larger companies do consider supply chain water risk in selecting suppliers. One company's largest exposure concerned water devoted to feed production for livestock and, as a result, informed water reduction goals. Another large company assessing its 50 largest water-using facilities considered water a minor factor (<1% of global operations) and often passed water risks to suppliers. Another company concluded that because operations could continue for 6-10 months without water, it was not a significant business concern.
Past exposure	One company noted that operations within California have faced four-fold price increases for water when usage exceeded the facility's allotment. This price penalty prompted investments in water metering and storage for reclaimed water.
Water risk identification	Some companies periodically conduct a global water-risk survey that assesses local and regional water stress, often highlighting operations and facilities at risk. However, the water-saving measures identified at these facilities are not transferred to other operations (e.g., risk in water-stressed areas can supersede improvement costs).
Risk mitigation measures	Some respondents either use or are considering using an internal price of water to make business decisions. Often, these same companies include long-term water planning measures within their business planning activities. Mitigation strategies include identifying alternative water sources and opportunities for conservation, and reuse within operations.
Water goals	One company established water withdrawal goals for each facility, specifically to reduce usage annually by 1% on a production-normalized basis. Other examples of goals include a 25% water use reduction within facilities and a 20% water intensity reduction by 2020.

2. Water Use Estimates to Support Risk Analysis

Section 2 Summary

- Reliable, usable, and accurate water data for plant and sectoral-level water use does not currently exist for the U.S. manufacturing industry.
- Numerous past methods have been used to estimate water use within manufacturing plants, but they are inconsistent with one another and present only a snapshot in time that does not reflect changes in industry.
- Past papers (e.g., McCall et al. 2021) have proposed new data requirements for performing risk and resiliency analyses to determine the U.S. manufacturing sector's risk with respect to water use.
- Section 2 outlines physical availability and thermal risk methodologies that would benefit from up-to-date water data.
    - Section **Error! Reference source not found.** demonstrates that the primary metals, fabricated metals, transportation equipment, petroleum and coal products, and plastics and rubber manufacturing subsectors are at the greatest risk of physical water shortages based on concentrations of water intake in water-stressed regions.
    - Section **Error! Reference source not found.** shows that for the facilities evaluated, a 0.5°C increase in surface water temperatures would lead to a 2%–12% reduction in cooling capacity. A 3°C increase would lead to a 15%–72% reduction in cooling capacity.
- Elements of Section 2 draw on the following work published by report authors: McCall et al. (2016), Rao et al. (2017), Rao, Sholes, and Cresko (2019), Armstrong, Garcia, and Nimbalkar (2020), Fuchs and Rao (2021), and McCall et al. (2021).

2.1 Introduction

Previous attempts to collect and synthesize official statistics on industrial water use have expanded knowledge while revealing significant data gaps. For instance, Becker (2016) analyzed the U.S. Census Bureau's Survey of Water Use in Manufacturing (SWUM) conducted from 1973 to 1978, uncovering patterns of water withdrawal and recirculation. Unfortunately, SWUM lacks continuity with current practice, and previous water use intensities (water volume per dollar of sectoral production) may no longer apply due to technological improvements. The United States Geological Survey (USGS) *Circular* series publishes water use estimates for the industrial sector every 5 years. Its dataset includes observations from state-level efforts and estimates with varying levels of accuracy (Dieter et al. 2018). Moreover, it reports only self-supplied industrial water uses. Boero and Pasqualini (2017) used USGS datasets to estimate industrial water coefficients at a more disaggregated spatial scale, following the U.S.

Environmental Protection Agency (EPA) level II ecoregions.[6] Others reviewed Canada's Industrial Water Survey (IWS) to understand manufacturers' source water intake and recirculation patterns (Bruneau, Renzetti, and Villeneuve 2010; Dupont and Renzetti 1998; Dupont and Renzetti 2001; Renzetti 1993) or used Canada's water survey data and sectoral employment to disaggregate U.S. industrial water uses to county-level and 3-digit NAICS code resolution[7] (Rao et al. 2017). Other attempts to collect and report data include the DOE-sponsored Industrial Assessment Centers (IACs) program,[8] in which universities aid small- to medium-sized facilities in conducting energy and water assessments (Armstrong, Garcia, and Nimbalkar 2020).

However, despite these efforts, data gaps limit the capacity to estimate risk and formulate strategies for realizing water security (Cantor et al. 2018; Sadoff et al. 2015). Consistent data collected over time, at a refined spatial resolution, and for different economic sectors would support resource management, benchmarking, policy development, and informed decision-making under uncertainty. Improved data availability would enable markedly better analyses of the manufacturing water risks highlighted in Section 1 and advance the understanding of appropriate risk mitigation and resilience strategies. Section 2 reviews the current knowledge of water characteristics concerning intake and discharge before presenting facility-level data collection challenges and how technology innovation can help overcome these hurdles.

As noted in Section 1.2, the United States is one of the world's largest users of industrial water (FAO 2021). In 2015, the authors estimate the manufacturing sector accounted for about 6% of total U.S. water withdrawal, including 5% as self-supplied withdrawal from surface-water and ground-water sources (Dieter et al. 2018) and 1% through public water supplies (Becker 2016; Solley, Pierce, and Perlman 1998) for a total of 19.5 BGD. For context, total water withdrawals in 2015 were 322 BGD (Dieter et al. 2018). To understand manufacturing water withdrawal volumes relative to other sectors, see Figure 2.1 for the breakdown in 2010. Although national-level manufacturing water use data are scarce, past national surveys (Kenny et al. 2009; Becker 2016), representations of water use by other nations (Renzetti 1993), and corporate sustainability reporting (CDP 2018) show there is heterogeneity in water use volumes, water sources, water quality requirements, reuse and recirculation, and disposal practices across sectors and regions. Currently, accurate, up-to-date, and comprehensive data are unavailable for manufacturing water withdrawals, consumption, quality requirements, reuse within a plant, and discharge volumes and quality.

[6] The EPA has identified 4 levels of ecoregions—areas where ecosystems (and the type, quality, and quantity of environmental resources) are generally similar. https://www.epa.gov/eco-research/ecoregions
[7] NAICS uses a hierarchical structure. Within the manufacturing sector—the 2-digit codes of [31-33]—there are 21 subsectors denoted by 3-digit codes and 346 6-digit codes (the most detailed level of classification that encompasses industry group, NAICS industry, and national industry in addition to subsector).
[8] U.S. DOE's Industrial Assessment Centers: https://iac.university

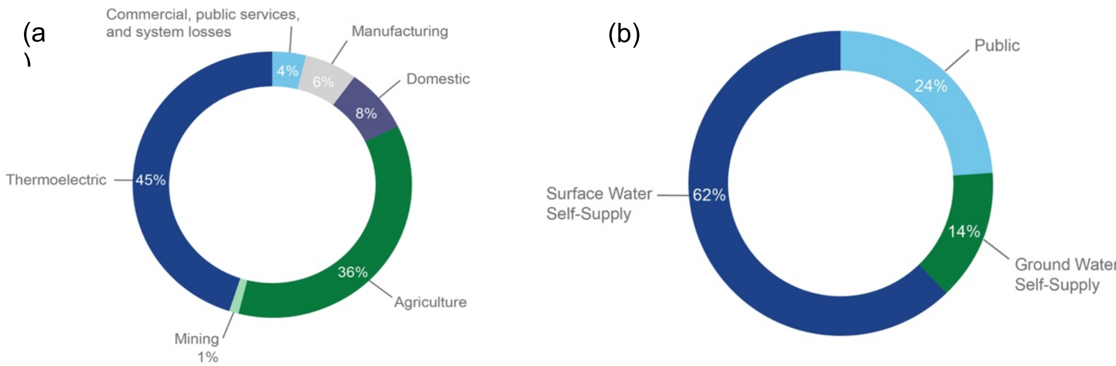

Figure 2.1 2010 manufacturing water use as share of total U.S. water use (a) and by source (b)
Figure source: Rao et al. (2017)

Within the U.S., manufacturing sites tend to concentrate in specific regions, resulting in heterogeneous water demand across states and watersheds. In addition, higher spatial disaggregation of manufacturing water demands—by county or 8-digit Hydrologic Unit Code (HUC-8) subbasins[9]—reveals an uneven distribution of water demands. As shown in Figure 2.2, Indiana, Louisiana, and Texas withdrew the greatest volumes of water for manufacturing in 2014. However, withdrawal within these states was not uniform but concentrated in certain areas. In Texas, for example, manufacturing water use was concentrated in the greater Houston area (Brazoria County), with little withdrawal for manufacturing in West Texas.

Water withdrawals for manufacturing-specific activities are only a small percentage (6%) of the U.S. total, compared to a significant share for some units at the sub-state level. Indeed, Rao et al*.* (2015) found that manufacturing water use makes up over 75% of water withdrawals for 60 U.S. counties.

Within the manufacturing sector, five subsectors dominate water use. Of the 20.9 BGD for manufacturing, pulp and paper withdrew the most (28.8%), followed by primary metals (26.2%), chemicals (20.5%), petroleum and coal products (12.8%), and food processing (6%). Figure 2.3 shows manufacturing water use by subsector and state, illuminating the industries withdrawing water by region. Within Indiana, which withdraws the most water of any state, primary metals is the lead manufacturing subsector for water withdrawals, likely due to the large volume required for once-through cooling. In Louisiana and Texas, petroleum refining and chemicals withdraw the most water of all manufacturing subsectors. In other states, one industry dominates manufacturing water withdrawal (e.g., pulp and paper in Maine).

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[9] USGS defines watersheds using a national hierarchical system based on surface hydrologic features, which delineates 22 regions (2-digit hydrologic unit code [HUC]), 245 subregions (4-digit), 405 basins (6-digit), and ~2,400 subbasins (8-digit). https://nas.er.usgs.gov/hucs.aspx

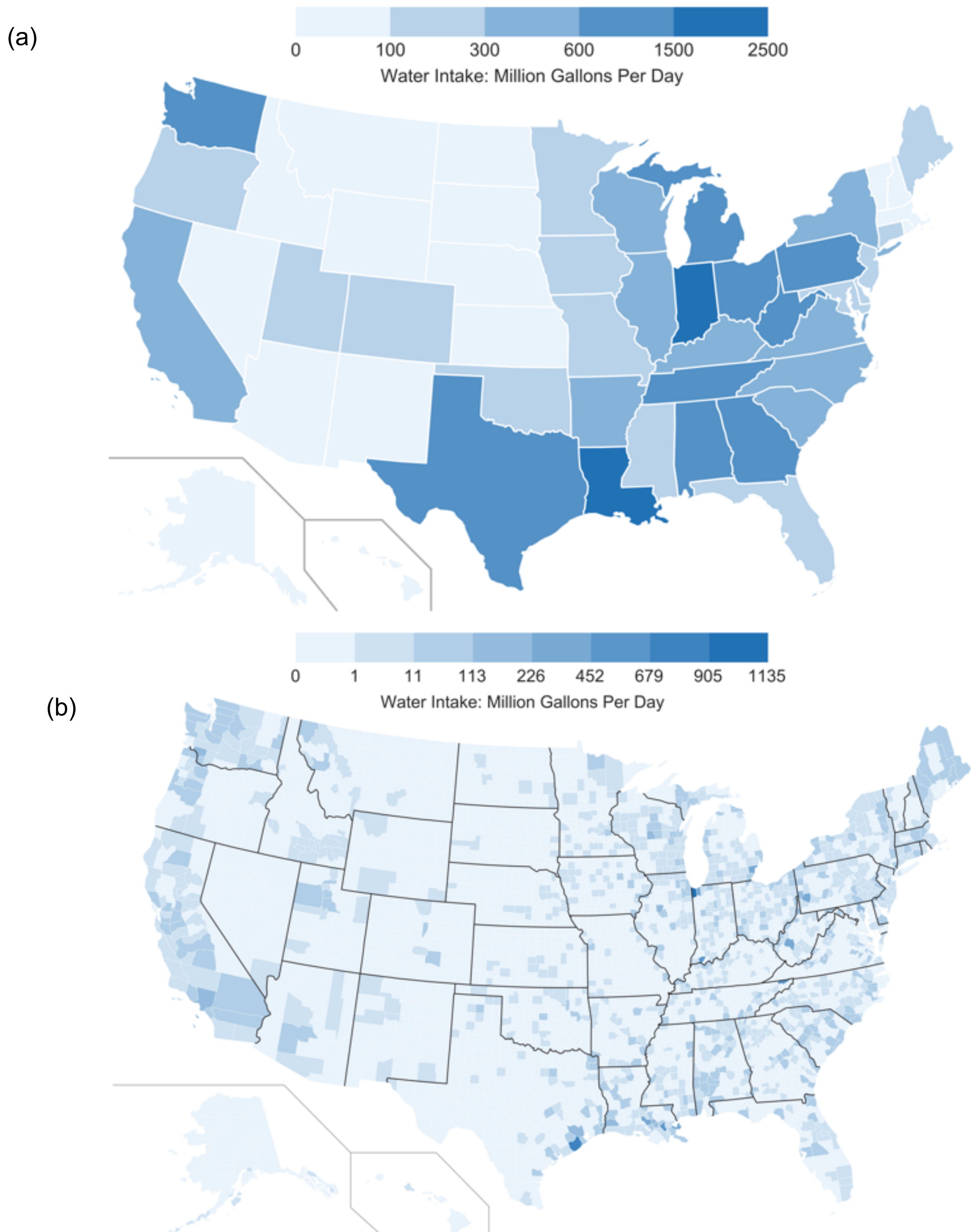

Figure 2.2 Manufacturing water use by state (a) and county (b)
Figure source: Rao et al. (2017)

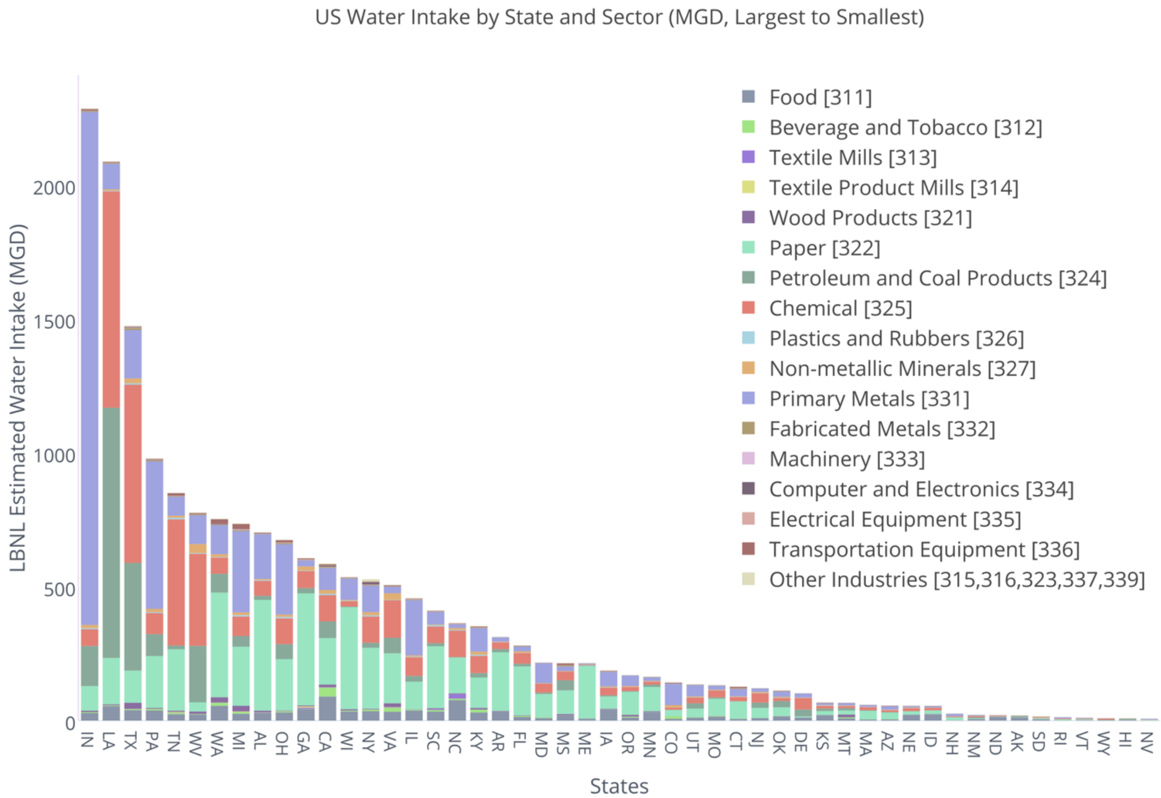

Figure 2.3 Estimates of manufacturing total water intake by state and subsector
NAICS code indicated in brackets
Figure source: Rao, Sholes, and Cresko (2019)

The authors based the estimates in Figure 2.1–Figure 2.3 and the accompanying discussion on data from the USGS, in conjunction with manufacturing demographics from U.S. Census and Canadian water withdrawal characteristics from Statistics Canada.[10] As such, these estimates carry an error and a degree of unknown uncertainty. Limitations of the current publicly available data preclude the research community from accessing direct (i.e., not estimated) information about how manufacturers use water and how that use impacts watersheds, with the latter being a key driver of risks. However, understanding these risks is essential to the manufacturing sector's adaptation to future water-related changes. Section 2.2.1 describes the state of data availability on U.S. manufacturing water use.

Finally, at the individual manufacturing plant level, publicly available data can be found for some of the plant water flows illustrated in Figure 1.1. Flow 1 data can be ascertained and compiled from utility water bills but is not readily available. Flow 2 data are available from the USGS water survey (Dieter et al. 2018) at the county level but only subdivided into eight macro sectors (e.g., industrial, power, agriculture). At any given plant, Flows 2 and 3 (the volume of self-supplied water) data are likely unknown, as this water is often not metered and is "free" to the manufacturer except for pumping, treatment, and permitting costs. Self-supplied water can often make up a larger share of withdrawals than municipal flows (Solley et al. 1998). For Flows

[10] Canada's national statistical agency https://www.statcan.gc.ca/en/start

4–5, data are currently unavailable, except from the few facilities that monitor them. Flows 6, 7, and 8 data are somewhat available at a facility level through the EPA's National Pretreatment Program (NPP); however, that dataset is unavailable in a readily usable form, and it has inconsistencies (Fuchs and Rao 2021). Flow 9 data, perhaps the most readily available at a facility level, are found in EPA Discharge Monitoring Reports (DMR). However, there are concerns with data quality for some volumetric flows, which are not often metered (but constituent information is well understood if the Clean Water Act regulates the constituent). Sections 2.2–2.4 review data availability for each labeled node in Figure 1.1 in greater detail.

2.2 Water Intake

Portions of this section appear in a recent peer-reviewed article in *ACS ES&T Water* (McCall et al. 2021).

2.2.1 Availability of National Data

Researchers have made multiple attempts to synthesize data on manufacturing water use. For instance, Becker (2016) analyzed the microdata of the discontinued SWUM and found patterns of water withdrawal and recirculation. Unfortunately, the water use intensities generated (water volume per dollar of sectoral production) may no longer apply because of technological improvements, new product lines and specifications, process changes, and other changes to the entire manufacturing sector. Also, it is difficult to compare certain sectors in operation now with their 1970s counterpart (e.g., electronics and semiconductors). Concurrently, from the 1950s through the present, the USGS *Circular* series has published self-supplied water use estimates for the manufacturing sector based on a mixture of state-level data reporting efforts and modeled estimates. However, these estimates do not disaggregate by subsector or industry, limiting their utility in answering any of the four questions posed by Dieter et al. (2018).

The lack of consistent sampling and reporting of manufacturing water use has motivated attempts to estimate and disaggregate manufacturing water data by combining disparate datasets with estimates that cannot be validated. Estimation methods usually involve simple regression models and extrapolation of water use coefficients (i.e., m^3/ton of production, m^3/employee, m^3/USD) based on one primary source of water use data at a national level or at a high sectoral aggregation level (3-digit NAICS codes) and variables obtained through U.S. Bureau of Economic Analysis (BEA) (e.g., sectoral gross production), U.S. Census Bureau (e.g., population), or U.S. Bureau of Labor Statistics (e.g., sectoral employment). A major limitation of extrapolating water use coefficients is that it neglects the effect of specific spatial, sectoral, or temporal factors such as climate, resource availability, and technological changes over time. In general, estimation methods are prone to high uncertainty because of errors intrinsic to surveys or census data, strong assumptions in estimation models, and error propagation. Table 2.1 presents recent national-scale studies that attempted to derive water use for industrial sectors. Table 2.1 is not exhaustive, representing only recent and relevant studies for national-scale estimates of industrial water use.

Table 2.1 Recent Water Use Estimation Studies

Study	Scale	Method	Main data source	Limitations
Marston et al. (2018)	• 117 areas (Commodity Flow Survey areas) • 378 industries • For year 2010	Allocation based on employment	• USGS estimates of Canadian water use parameters • IWR-MAIN Water Demand Forecast Manager Software[11] consumptive factors	Single variable allocation method; low correlation with water use at a specific facility
Yang et al. (2017) and U.S. Environmentally-Extended Input-Output (USEEIO) models	• 6-digit NAICS • National level • For year 2010	Allocation based on gross domestic product (GDP) and employee compensation; reported as m^3/USD	• Canadian Industrial Water Survey • U.S. purchase of water, sewage, and other systems	Based on USGS and Canadian data at 3-digit NAICS resolution at the most; national-level data availability
Blackhurst, Hendrickson, and Vidal (2010) and Economic Input-Output Life Cycle Assessment (EIO-LCA) method	• 6-digit NAICS • National level • For year 2005	Allocation based on sectoral employment; reported as gallon per million USD	• Canadian Industrial Water Survey • USGS estimates	Allocation of public supply assumes geographically uniform water price; to allocate self-supplied water, assumes domestic industrial practices are similar to Canadian
Boero and Pasqualini (2017)	• 3-digit NAICS • County level; Level II EPA ecological regions • For year 2010	Linear regression using regionalized county-level GDP	• USGS estimates	Industrial water from USGS dataset is the industrial self-supplied water plus all non-domestic public supply; regression only uses GDP as explanatory variable for water use
Rao et al. (2017)	• County, 3-digit NAICS	Single metric, intensity-corrected using USGS data	• USGS estimates • Canadian Industrial Water Survey	Includes construction; cannot validate subsector or county-level estimates

[11] The IWR-MAIN Water Demand Management Suite is a CDM Smith computer program that projects future industrial and municipal water demands: http://www.dynsystem.com/IWR-MAIN/

To investigate the utility of available data, the authors undertook the following data collection and analysis efforts:

1. Perform a bottom-up, state-level analysis to collect disparate datasets.
2. Review information in the Industrial Assessment Center database.
3. Compare water use coefficients from past analytical studies to determine sectoral accuracy.
4. Explore multi-variable regression methods to determine achievable improvements.

Sections 2.2.2–2.2.4 describe these efforts.

2.2.2 Availability of State Data

To fill in data gaps, the authors compiled facility-level water withdrawal data from individual states and at an industrial level to perform a bottom-up water accounting analysis. This approach consisted of adding up the water used by individual facilities by subsector and validating it by comparing the summation against aggregated withdrawal data from the EPA DMR.

Because state water agencies determine the majority of water withdrawal regulations, they vary by state, complicating data consolidation efforts. Compiling water withdrawal data required the following data collection and processing steps:

1. Perform a cursory search of online data available at state permitting agencies.
2. If data were not readily available, contact by phone and email the relevant employees at the state agencies to locate data.
3. If data were available, format it to support comparing data across states.

At the time of data collection, only 19 states had water withdrawal values available at the facility level. Other states compiled data at the county level or aggregated into one macro sector, similar to the USGS water use *Circular* series. Overall, the analysis found no standard reporting methods on a state-by-state basis.

Of all available state data, only one state (North Carolina) published data at a facility level that contained water withdrawal, water discharge, and NAICS information. Three states (Texas, New Hampshire, and Maine) collected water withdrawal values and NAICS identifiers, but no discharge data. Of the remaining 15 states with water data at a facility level,[12] no state reported the NAICS codes. The authors used available facility identifiers or geo-coded addresses to match discharge data from the DMR. However, this was only widely available for 7 of the 15 state-level datasets, representing only 3% of facilities within the overall DMR dataset.

As a validation step, the authors aggregated industry-level withdrawal and discharge data available in 2010 and compared it with subsector-level withdrawal and discharge values. Of the most water-intense NAICS codes in the compiled dataset, the summation of withdrawals across an industry was an order of magnitude less than the discharge volumes from the EPA DMR,

[12] Georgia, Indiana, Iowa, Kentucky, Maryland, Massachusetts, Michigan, Minnesota, Missouri, Mississippi, New Jersey, New York, Oklahoma, Tennessee, West Virginia

highlighting data gaps in the bottom-up analysis. This result could mean that the dataset did not capture all water withdrawals (e.g., self-supplied, surface, ground, purchases), the datasets did not compare similar timeframes, and/or the EPA DMR data reflected inaccurate reporting. Whatever the case, the data were unusable for any meaningful analysis, highlighting the need for homogenized protocols for data collection and integration among agencies.

2.2.3 Existing Methods and Comparisons

2.2.3.1 Comparing Water Use Coefficients from Past Analytical Studies

As introduced in section 2.2.1, researchers have attempted to estimate the average volume of water used by industrial sectors from datasets such as the Canadian IWS or USGS publications. Studies often derived these estimates from simple regression methods or water use coefficients based on the production or employment of the sector (i.e., m^3/ton or m^3/employee). However, directly applying water use coefficients neglects the effect of specific spatial, sectoral, or temporal explanatory variables such as climate, resource availability, policies, risks, sectoral environmental stewardship, and technological changes over time.

Researchers have traditionally used environmentally extended input-output (I-O) methodologies to estimate the direct and indirect water use of products along supply chains (Garcia et al. 2020). These models require employing direct water use coefficients (referred to as satellite tables or externalities in economics parlance) for each sector. Therefore, developers of I-O models have attempted to derive water use coefficients in the units of water volume needed to produce a given amount of economic output (m^3/$). I-O models, such as the EPA's Environmentally-Extended Input-Output models and Carnegie Mellon University's Economic Input-Output Life Cycle Assessment (EIO-LCA) apply the water use estimates from Blackhurst, Hendrickson, and Vidal (2010) as a reference for water use coefficients.

The I-O framework allows for calculating direct and indirect impacts associated with an economic activity. Direct water withdrawals for a sector are the withdrawals by the sector itself, while indirect water withdrawals are withdrawals in the supply chain of the sector. The I-O method can model the intersectoral dependence and, therefore, enable the calculation of the supply chain withdrawals associated with a sector. Estimating a sector's water withdrawals uses the water withdrawal coefficients (in terms of m^3/$) along with the economic output data for the sector. The major steps for an I-O analysis are as follows:

- Step 1: Determine water withdrawals/consumption coefficients (m^3/$) for manufacturing subsectors.
- Step 2: Use this vector along with the direct requirement matrix obtained from BEA input–output accounts data to calculate direct and indirect water withdrawals associated with an economic activity.

Equation 1 from Blackhurst, Hendrickson, and Vidal (2010, 2128) shows the calculation for total water use of a sector due to an economic activity.

$$W = (I - A)^{-1}XF$$

Equation 1

Where:

W= Total (direct + indirect) water use of a sector (m^3) due to purchase X ($)

A = Direct requirement matrix or economic input–output matrix (unitless)

I = Identity matrix (unitless) is a square matrix with all diagonal elements as 1 and all off-diagonal elements as zero.

F = Diagonal matrix with elements equal to water per dollar of output for each sector (m^3/$)

X = vector of purchases ($)

The direct requirement matrix, A, is a square matrix whose coefficients represent the intersectoral dependence. Table 2.2 illustrates a simple two-sector hypothetical "A" matrix. The coefficients in this example mean that producing one dollar of output in Sector 1 (Agriculture) requires 15 cents of output from Sector 1 and 20 cents of output from Sector 2 (Manufacturing).

Table 2.2 A Hypothetical Two-sector "A" Matrix

Miller and Blair (2009)

	Sector 1 (Agriculture)	Sector 2 (Manufacturing)
Sector 1 (Agriculture)	0.15	0.25
Sector 2 (Manufacturing)	0.20	0.05

Studies recommending this method for water use estimation have estimated water withdrawal coefficients for different economic subsectors. Most of these studies and others base their estimates on Canadian industrial water use characteristics. They allocate the self-supplied industrial water estimates from USGS water surveys to different manufacturing subsectors based on the Canadian data. Table 2.3 lists the studies and their data sources considered in this analysis.

Table 2.3 Water-Use Estimation Studies and Data Sources

	USEEIO (Yang et al. 2017)	Blackhurst, Hendrickson, & Vidal (2010)	Boero & Pasqualini (2017)	Marston et al. (2018)
Water withdrawal/ consumption	Water withdrawal (m^3/$2013)	Water withdrawal (gal/$M)	Water withdrawal (gal/GDP$ 2010)	Water consumption (m^3/$1000)
Sectoral resolution	~380 sectors (6-digit NAICS)	~420 sectors (6-digit NAICS)	~65 sectors (3-digit NAICS)	~380 sectors (6-digit NAICS)
Spatial resolution	National	National	National; 20 EPA ecological regions	117 Commodity Flow Survey (CFS) areas
Data sources	USGS Water Survey (2010)	USGS Water Survey (2000)	USGS Water Survey (2010)	USGS Water Survey (2010)
	BEA Input–Output tables (2007)	BEA Input–Output tables (2002)	BEA Input–Output tables (2010)	Canada Industry Statistics (2017)
	Canadian Industrial Water Survey (2010)	Canadian Industrial Water Survey (2005)	Quarterly Census of Employment and Wages (QCEW)	Water consumption coefficients – U.S. Census Bureau (1986)
	Canadian Industry Statistics	Canadian Industry Statistics		Numerous sources for inter-CFS area transfers
		U.S. Census of Employment & Wages (2002)		

Estimates for water use coefficients (m^3/$) from studies were converted to 3-digit NAICS sectoral resolution for the manufacturing sector using the weighted average approach.

Figure 2.4 represents a range of water coefficients calculated from (1) past studies and their ranges (Marston et al. 2018; Yang et al. 2017; Blackhurst, Hendrickson, and Vidal 2010; Boero and Pasqualini 2017), (2) 2015 Texas industrial water survey data (Texas Water Development Board n.d.), and (3) Canadian industrial water use statistics (Statistics Canada 2020; Statistics Canada 2017; Statistics Canada 2015). The different datasets present a wide range of water use coefficients, which is even wider for most water-intensive industries. The wide variability in estimates of water use by facilities may reflect several factors, such as plant age and technology, different study boundaries and respondents' understanding of those boundaries, product type, availability of water metering, and company standards. However, the available data is insufficient to validate these numbers or provide an accurate estimated range and standard deviation of water use by industry, let alone plant.

It is worth noting that economic flows between subsectors may not always mirror the physical water flows behind the material exchanges between those subsectors, creating opportunity for data distortions. While this range variability may highlight inaccuracies in data, it could also provide evidence that water use across facilities within the same subsector utilize water differently, leading to the range, but a touchstone dataset to validate this rationale is unavailable. Even single-point estimates from the latest Texas data and the widely used biennial Canadian statistics are largely outside past study ranges, likely because of different data frames. Not only is the single-economic-output-based metric inadequate to estimate water use at the 3-digit NAICS industry level, but the temporal and spatial considerations may also be essential to capture, as each study represents only a snapshot in time.

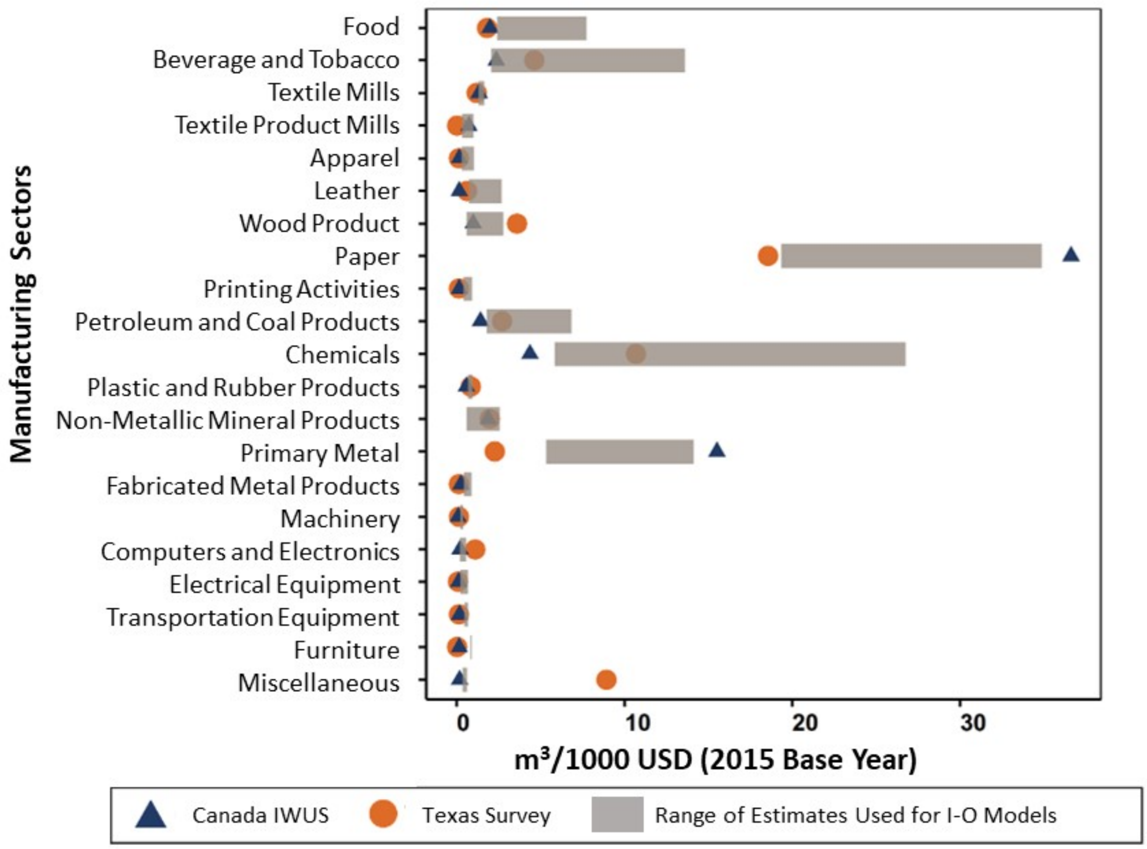

Figure 2.4 Comparative water withdrawal coefficient estimates

2.2.4 Results from More Advanced Methods

In an attempt to fill in the data gaps created by the inadequacies of existing data and the uncertainty associated with existing estimates, researchers developed and executed advanced estimation techniques. Where previous attempts in the literature generally focused on directly collecting water use data or using metrics that normalize water use to a single variable, advanced methods exist that seek to find correlations between multiple variables that may drive water use and actual water use. The authors applied these methods to facility-level and national-level data to develop models that could more accurately predict manufacturing water use at the sector, regional, or temporal scales. Sections 2.2.4.1–2.2.4.2 describe these efforts and results.

2.2.4.1 *Regression Models Using the Industrial Assessment Center Database to Predict Water Use and Cost across U.S. Manufacturing Subsectors*

This section characterizes manufacturing water use data from the DOE-sponsored database of IACs and the methods and limitations of using it to predict water use.

Data Source

IACs are university-based organizations that provide free audits to small- and medium-sized manufacturing facilities across the United States to identify energy and water efficiency improvements and waste reduction opportunities. The IAC program collects utility data from participating manufacturing facilities in an effort to "identify opportunities to improve productivity and competitiveness, reduce waste, and save energy" (DOE 2020).[13] The IAC database contains data from 19,085 assessments collected over 40 years. In addition to water and energy use/cost data, IACs collect data on sales, facility size, production, operation hours, number of employees, and location. The present study primarily aimed to develop regression models based on these independent parameters and predict water use and cost by manufacturing subsectors (Armstrong, Garcia, and Nimbalkar 2020). The study revealed the large variability in publicly supplied water use in small and medium-sized facilities within 3-digit NAICS manufacturing subsectors. However, only 664 assessments in the database (<1%) included water use information, mainly because IACs only started collecting water data in 2016. Figure 2.5 shows the frequency of audits that collected water utility data per state, year, and manufacturing subsector.

[13] To receive an IAC assessment, facilities must have an annual energy spend between $100K and $2.5M, gross annual sales less than $100M, fewer than 500 employees, and be near an IAC (150–180 miles), although exceptions can be made.

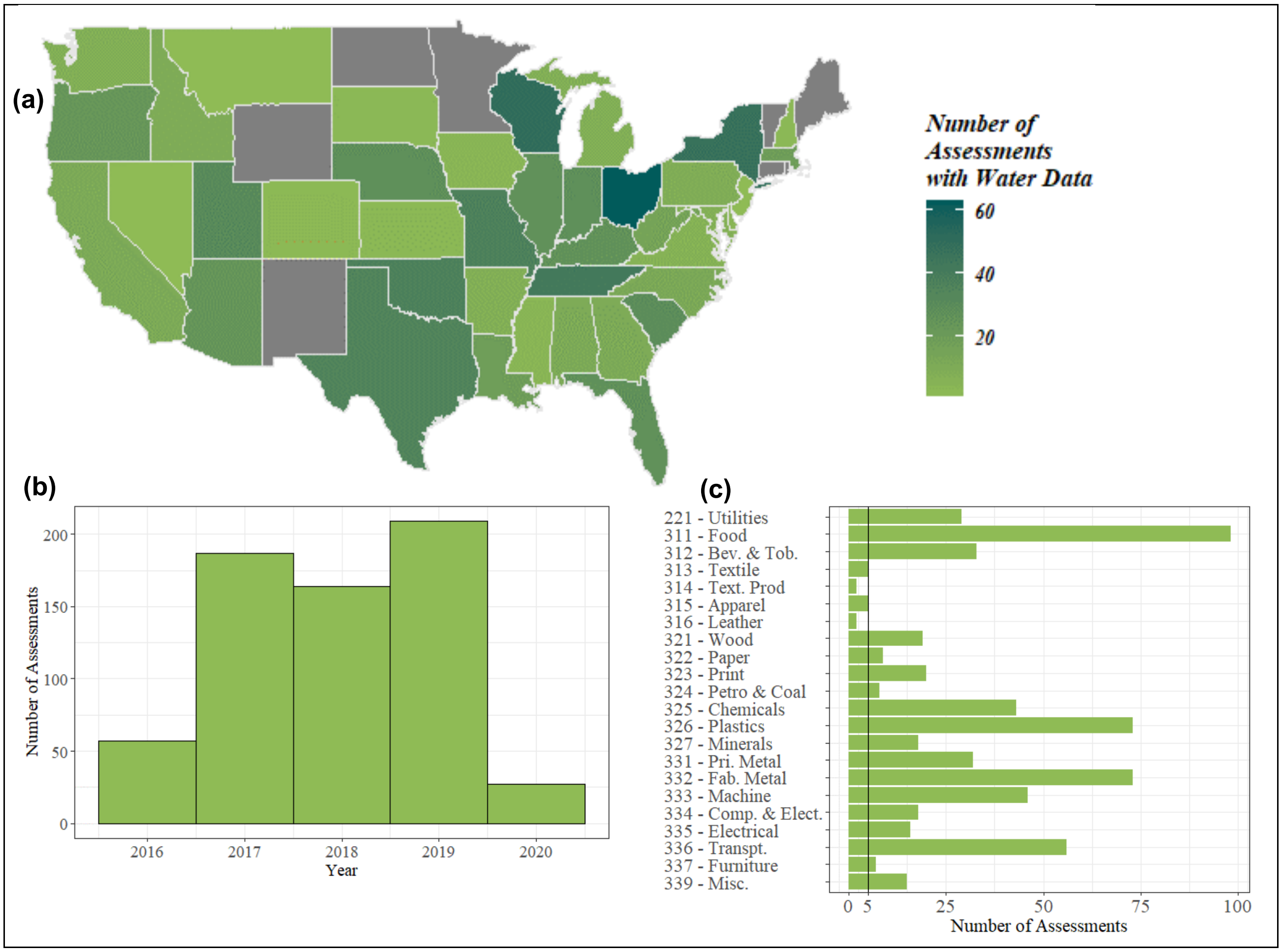

Figure 2.5 Frequency of IAC water use audits across a) states, b) year, and c) manufacturing subsector

Analysis

The authors conducted exploratory data analysis in three phases: (1) attempt to identify potential outliers, (2) systematically select explanatory variables, and (3) test regression models. They found the IAC data highly skewed and identified a few factors responsible for the highest water use or cost. They employed multiple methodologies to remove potential outliers from each industry group: first, by removing water use data outside three standard deviations of the mean for that industry, and second, by applying the median absolute deviation (MAD) approach to account for the skew of the data.

Next, the authors analyzed post-processed data through a stepwise regression model to identify statistically significant explanatory variables for the regression analysis. Variables removed from the analysis included weakly correlated variables such as electricity and natural gas use, and the production data of each facility in the dataset due to inconsistent reporting of units across facilities and subsectors. Ultimately, the team determined the analysis of water use reported for IAC assessments to be unsuitable for generalized analysis of 3-digit NAICS manufacturing subsectors. The analysis of the water data from 613 IAC assessments could not generate acceptable regression models for all NAICS codes, and some it did create had negative coefficients.

Additionally, the authors observed several problems in the dataset before and after conducting the analyses. Using cost and use data to estimate the unit cost of water revealed several sites with water costs substantially different from the typical national range of \$0.25 to \$2 per m^3 (\$1 to \$8 per thousand gallons (kgal), FEMP 2017)—likely due to data entry errors. Attempting to remove these outlier data points resulted in datasets too small for analysis. Additionally, Tukey tests for water use and cost, as well as the explored predictor variables,[14] showed that, for most combinations, the in-group variance was significantly larger than the out-group variance (at a 95% confidence interval), showing that segregating this dataset by NAICS code will likely not produce useful predictive models, regardless of other assumptions. This result is likely due to the focus of IAC assessments on small and medium manufacturing, which probably have more in common with each other than larger manufacturing sites.

Conclusion

As mentioned, there is no consistent production variable available for use in analysis. While the study used sales, production hours, number of employees, and facility area as proxies, many external factors affect these variables. Finally, the IAC assessment only collects water utility bills, not overall water use. Hence, although an opportunity exists to use water data collected during the IAC assessments, robust water use or cost-predictive analysis requires increasing the quantity and improving the quality of data collected. Given the multiple concerns surrounding unreliable data points, researchers need to conduct a more thorough investigation to detect patterns and outliers before using these estimates to predict facility-level water use. Section 2.4 presents some facility-level data collection challenges relevant to the water-related portion of IAC assessments.

2.2.4.2 Multi-Variable Regression Methods Using Statistics Canada Data to Predict Manufacturing Water Intake across Canadian Manufacturing Industries

Another attempt at applying advanced estimation techniques aimed to develop a means for predicting manufacturing water intake within the manufacturing sector—particularly for Canadian manufacturing industries. The authors carried out multi-variable regression analysis to understand which underlying business and climate-related factors may play the most significant roles in determining water intake needs among these selected industries and how each factor's level of influence may vary across industries. Using these factors as predictor variables in these models, the team identified statistical relationships between manufacturing water intake and the chosen predictor variables and used them to predict water intake for each industry. Predictor (independent) variables were specifically chosen to be utilized for both the Canadian and U.S. manufacturing sectors such that U.S. county-level data were available, so that these methods may subsequently be used to inform U.S. manufacturing water intake at the

[14] Tukey's test is a statistical test using a single-step multiple comparison procedure to identify means that are significantly different from one another. It simultaneously compares all possible pairs of means to identify any difference between means greater than the expected standard error. https://online.stat.psu.edu/stat502/lesson/2/2.3

county level. Predictor (independent) variables utilized in these models included:

- Number of employees tied to an industry—used to estimate water intake when water use and employee count are either directly or indirectly correlated. For example, in a direct correlation, the dominant use of water is for domestic purposes; in an indirect correlation, the size of the facility dictates the magnitude of water use, and can be quantified by the number of employees.
- Number of unique establishments—used when the magnitude of water use by facilities within a sector is similar.
- Cooling degree days—a metric to quantify the number of hours cooling is needed annually for a given location; used to predict water intake when cooling is the dominant water use.
- Heating degree days—a metric to quantify the number of hours heating is needed annually for a given location; used to predict water intake when heating is a dominant water use.

Data Source

The data source for the manufacturing water intake quantities and principal statistics used to inform the chosen predictor variables was Statistics Canada's manufacturing industry data tables for NAICS codes 31-33. All variables were collected at two-year intervals from 2005 through 2015, based on Statistics Canada's biennial industrial water intake survey. The authors retrieved the data from the Statistics Canada Socioeconomic Data database,[15] the primary source for time-series-based social and economic data. To capture the influence of climate on manufacturing water intake, they used cooling and heating degree days data sourced from weather stations in key cities for multiple regions across Canada. Canada Weather Stats sourced these data for the years matching those of the previously selected variables (2005 through 2015 at two-year intervals). Accordingly, these data fit the shape of four predictor variables across six observation years. Appendix A provides data sources for all variables used in this study.

Analysis

The authors applied multiple linear regression to the input data to find the impact of the chosen predictor variables on manufacturing water intake across a manufacturing subsector, the dependent variable. Specifically, stepwise regression in the "backward" direction was employed to find the most optimal set of predictor variables for each industry that yields the greatest predictive power, serving as a straightforward means of model selection. Through this method, permutations were run to test all possible combinations of predictor variables for each industry to obtain the combination that best explains the data, thus prioritizing variables with the strongest influence on water intake. Starting each permutation as a multiple linear regression with all predictor variables intact, variables that least represented the data, and thus held the least predictive power, were subsequently removed at each round.

[15] Previously known as CANSIM (Canadian Socio-Economic Information Management System)

Elimination applied the Akaike Information Criterion (AIC), which holds that there is a tradeoff between model quality and additional variables, similar to the concept of the adjusted R-squared. The AIC indicates how much predictive power (or information) would be sacrificed if a variable were removed, based on the idea that too many variables will increasingly compromise the validity of a model. Accordingly, this study used a stepwise regression model based on AIC to remove the variable with the lowest AIC from the full model with all predictor variables intact and continuing to do so until it produced the best model, meaning the most predictive reliability with the least number of necessary predictor variables. Eliminations continued until further eliminations would result in a higher AIC and, thus, lower predictive power. This result meant that the permutation model (technically a combination model since the order of predictor variables did not matter) could stop at three predictor variables if that was the best possible model, or two, or even one.

Recognizing that different industries could have models with different explanatory variables selected, the study identified the best model for each industry and used these regression models to predict water intake for the years 2005 through 2015. Differentials as absolute values were recorded between actual water intake and predicted water intake to note the accuracy of the optimized "best" models. Additionally, regression models with all variables intact (full models) were used to predict water intake for the years 2005 through 2015, with differentials as absolute values recorded between predicted and actual values. Lastly, the absolute difference (error) of predicted water intake value for the best models was compared with that of the full models to validate the performance and reliability of the model selection method.

While the study implemented stepwise regression to select the best model, it also detailed several criteria to support evaluating model reliability. Specifically, criteria for p-value and adjusted R-squared were set to validate each model based on its statistical significance and representation of the data, respectively. To determine if a model should be deemed sufficient, whether a full model or best model, a threshold of p-value: 0.2 and adjusted R-squared: 0.75 was set. The higher-than-typical cutoff for the p-value was selected to allow for indirect correlations of a predictor variable to the water intake to be included.

Conclusion

Though several of these implemented models showed significant explanatory power, both for full models and best models, the authors cannot conclude that manufacturing water intake can be accurately predicted across industries based on the majority of the models and the associated predictor variables. Table 2.4 shows the results from applying all five selected predictor variables and the stepwise regression approach using two thresholds for the adjusted R squared to each manufacturing subsector. Food manufacturing [311] and nonmetallic mineral product manufacturing [327] were unique in that their associated models with all predictor variables intact yielded excellent results, with p-values and adjusted R-squared values that significantly exceeded the designated thresholds, showing promise for using these models to predict manufacturing water intake from the chosen variables. A greater number of industries saw models improved through stepwise regression and the removal of unhelpful predictor variables, such as wood product manufacturing [321], paper manufacturing [322], and chemical manufacturing [325]. Interestingly, wood product manufacturing and paper manufacturing saw their most reliable models containing only one, and the same, predictor variable, namely, the number of employees. In fact, for the majority of industries for which the best model proved more reliable, the number of employees as a single variable was the most common selection, revealing a potential area of exploration for stakeholders looking to predict manufacturing water intake and providing confidence for those who have already used this variable (Rao et al. 2017). Still, it was often the case that an improved model saw an improvement for selected predictor variables only in p-values, passing statistical significance thresholds, but still showing an unsatisfactory R-squared. For these reasons, one cannot conclusively state that any one combination of predictor variables proved to be pervasively capable of predicting manufacturing water intake. Any speculation would need to be based on careful weighing of the tradeoffs between the significance of individual variables and the overall fit of the model itself, a means of determination requiring further data on manufacturing water use (e.g., water by end use).

The most significant drawback to this study is the small sample size of the observation data. The study had access to only 6 years of data due to limited survey data on manufacturing water intake. The small survey sample underpinning the statistical models limits their robustness and the conclusions that can be drawn from them. In fact, due to the small sample size, five predictor variables could not be accommodated, as a multiple linear regression of sample size “n” (in this case, n = 6) cannot accommodate “n-1” variables. Even with one additional observation year, the model would still likely have too few data points to be considered reliable by industry. In addition, a major difficulty in proving the reliability of the model lies in the lack of contextual input for each industry, noting how each predictor variable, such as workforce size or number of establishments, may hold unique meaning for each industry. Specifically, this would concern the issue of multicollinearity, where certain eliminated predictor variables could be highly correlated to another significant variable, thus indicating potential relationships between variables that are difficult to detect using these regression models alone, adding another layer of complexity. For instance, an industry’s number of employees may be most influential in predicting manufacturing water intake, and the number of establishments may not be nearly as influential; yet the number of establishments may still hold significant influence in determining the number of employees. Again, this consideration requires more refined and developed models to account for this nuance and complexity.

In light of the initial directives of this study, Table 2.4 condenses and synthesizes findings into a format that may be most useful for industry stakeholders, providing guidance on which predictor variables may best provide the most reliable results for each industry in terms of predicting water intake.

For each industry, this table details where it is appropriate to use a full regression model vs. an optimized “best” model through stepwise regression, followed by an indication of whether these best models pass p-value thresholds for significance of variables and goodness-of-fit. Lastly, the rightmost column suggests which predictor variables should be used to most accurately predict manufacturing water intake for each industry. Based on these results, it is clear that a more rigorous approach is needed. However, as with any statistical approach, the credibility of such an approach would greatly benefit from having a U.S. dataset against which to validate the models. Without validation data, statistical approaches will always result in an unknown level of uncertainty.

Table 2.4 Most Reliable Predictor Variables for Predicting Water Intake, By Subsector

Subsector [3-digit NAICS code]	**Full regression model**	**Stepwise regression** Adjusted R-squared >0.75	Adjusted R-squared >0.5	**Conclusion**
Food manufacturing [311]	Yes	*	-	Use all 5 predictor variables
Beverage and tobacco product manufacturing [312]	No	No	No	Use employees
Textile mills [313]	No	No	Yes	Use employees
Textile product mills [314]	No	No	Yes	Use employees
Wood product manufacturing [321]	No	Yes	-	Use employees
Paper manufacturing [322]	No	Yes	-	Use employees
Petroleum and coal products manufacturing [324]	No	No	No	Use employees
Chemical manufacturing [325]	No	Yes	-	Use establishments and cooling degree days (CDD)
Plastics and rubber products manufacturing [326]	No	No	No	None of the predictor variables are sufficient
Non-metallic mineral product manufacturing [327]	Yes	-	-	Use all 5 predictor variables
Primary metal manufacturing [331]	No	No	Yes	Use establishments and CDD
Fabricated metal product manufacturing [322]	No	No	Yes	Use employees
Machinery manufacturing [333]	No	Yes	-	Use employees
Transportation equipment manufacturing [336]	No	No	No	None of the predictor variables are sufficient
Miscellaneous manufacturing [339]	No	No	No	Use employees

* Blanks indicate that the criterion was not pursued because a more stringent criterion was met.

2.3 Water Discharge

A manufacturing facility interacts with its local environment via its discharge, shown as Flow 6 in Figure 1.1. The terminus of this discharge includes being sent directly back to the water source, back to the water source after on-site treatment, directly to the municipal wastewater facility, and/or to the municipal wastewater facility after on-site treatment. The water quality of wastewater discharge, rather than intake water, has greater environmental impact. Identifying the contaminants in the discharge water helps assess a manufacturing facility's impact on local water quality. This section reviews and compiles publicly available sources for discharge water quality and volume.

2.3.1 Wastewater Contaminants

This section summarizes work published in a peer-reviewed article in the *Journal of Industrial Ecology* (Fuchs and Rao 2021). The article reviews publicly available EPA wastewater guidelines, permits, and data on manufacturing wastewater constituents and reveals a lack of nationally representative data on manufacturing wastewater characteristics. This section summarizes EPA's industrial wastewater datasets to improve identifying contaminants by subsector.

2.3.1.1 Data Sources

EPA maintains two relevant national databases of industrial wastewater discharges under its National Pollutant Discharge Elimination System (NPDES) permit program, which began in 1972 under the Clean Water Act. NPDES permits allow facilities to discharge stipulated amounts of contaminants into receiving waters, with permit renewal required at least every five years. EPA's Integrated Compliance Information System (ICIS) contains DMR and Toxics Release Inventory (TRI) data, accessible through the Water Pollutant Loading Tool (EPA 2020a,b).[16]

DMR data cover "major" industrial and municipal dischargers in all point source categories that emit effluent directly to receiving waters (e.g., lakes, streams). The Electronic Code of Federal Regulations (eCFR) provides the regulatory definition of *major facility:* "any NPDES 'facility or activity' classified as such by the Regional Administrator, or, for 'approved State programs,' the Regional Administrator in conjunction with the State Director" (eCFR Title 40 Chapter 1/Subchapter D/§ 122.2). Based on a review, no single national definition of a major industrial facility exists. For example, the State of California defines a *major industrial facility* as one "determined based on specific ratings criteria developed by U.S. EPA/State" (California State Water Resources Control Board 2015). In another example, EPA Region 10 (Pacific Northwest) uses the EPA NPDES Permit Rating Work Sheet to designate major vs. minor facilities (EPA Region 10 2018). The worksheet scores facilities based on data provided for the following factors: toxic pollutant potential, flow/stream flow volume, conventional pollutants, public health impact, water quality factors, and proximity to near coastal waters; a combined score of equal to or greater than 80 results in the facility receiving a "major" designation (EPA 1990).

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[16] The Water Pollutant Loading Tool (Loading Tool) is a web-based tool that calculates and reports facility pollutant discharges in pounds per year or by monitoring period based on NPDES permit limit and DMR data.

TRI reporting is limited to industrial facilities in the manufacturing, electric power generation, and mining sectors that use a TRI-listed chemical in quantities exceeding annual threshold levels and employ at least 10 full-time equivalent employees. TRI-listed chemicals for each reporting year are available online; in 2020, this list comprised 33 categories and 755 individual chemicals.

Other potentially relevant data are those collected under the NPP, which governs commercial and industrial facilities discharging to publicly owned treatment works (POTWs), or municipal wastewater treatment plants. In the early 1980s, EPA found that up to one-third of priority pollutants entering U.S. waters stemmed from industrial releases into public sewers (NRC 2012). The General Pretreatment Regulations of the NPP established by the EPA in 1983 require POTWs to establish local pretreatment programs that enforce national pretreatment standards as well as any more stringent local requirements. Today, NPP is implemented as a partnership between EPA, states, and POTWs. At the time of writing, NPP data were available only as paper files or scanned PDFs at individual permitting authority levels (i.e., 36 individual states and EPA regions), instead of being available nationally in a consistent electronic format. These data could in theory be manually collated via a very labor-intensive process involving requests to individual permitting authorities. Table 2.5 summarizes the three datasets introduced in this section.

Table 2.5 Summary of EPA Data Sources for Manufacturing Wastewater

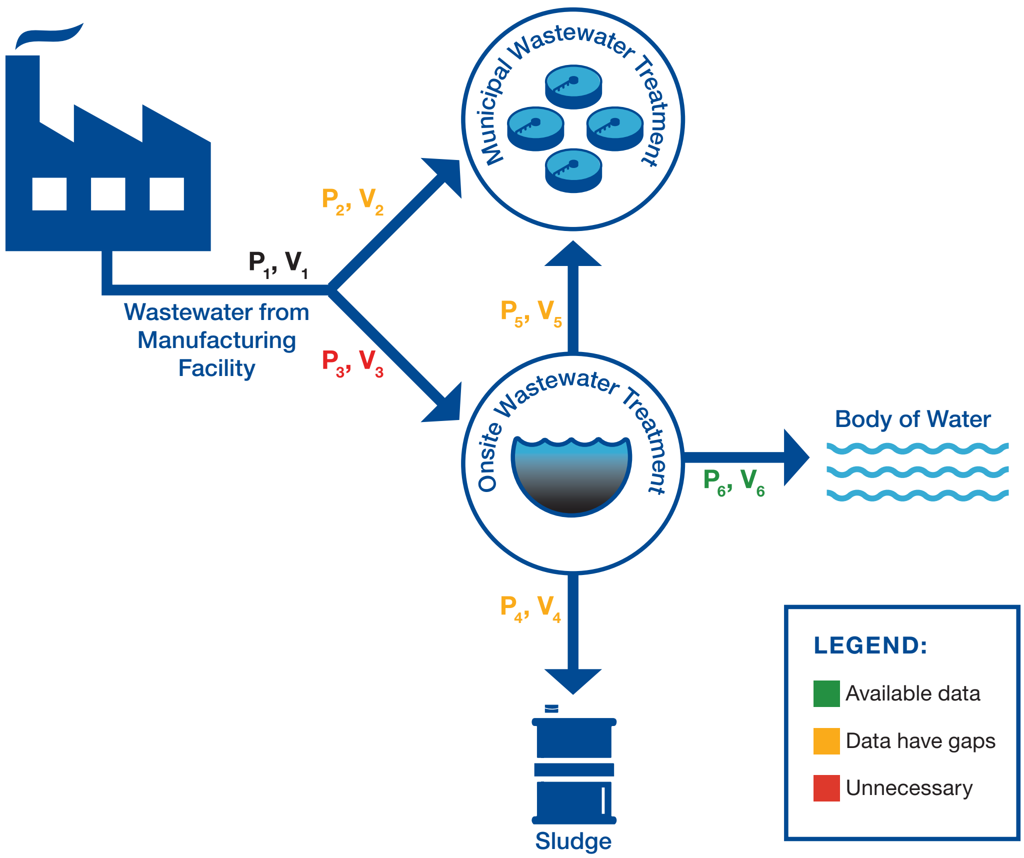
Data source	Who reports?	What is reported?	What is not reported?	Status
DMR	Over 60,000 industrial and municipal facilities discharging directly to receiving waters	Any pollutant discharged to receiving water that facilities are required by permit to monitor	Discharges from “minor” dischargers; releases to POTWs	Publicly available
TRI	Industrial facilities that discharge to POTWs, have >10 employees, and exceed reporting minimum	Toxic pollutants listed on the TRI-list (692 individual chemicals and categories)	Common contaminants (*e.g.*, Biochemical Oxygen Demand-BOD, Total Suspended Solids -TSS); volumes	Publicly available
NPP	Industrial and commercial facilities discharging to POTWs that make up ≥5% of POTW capacity, and/or exceed 25,000 gpd	• Toxics (defined in eCFR Title 40 Chapter 1/Subchapter N/§ 401.15.) • Conventional pollutants: BOD, TSS, fecal coliform, pH, oil and grease • Non-conventional pollutants	Unknown (see last column)	Not currently available in a consistent electronic format

2.3.1.2 Analysis

Figure 2.6 tracks the possible flow of wastewater discharges from a manufacturing facility to municipal wastewater and on-site treatment, the latter further discharging effluent to municipal treatment, to a water body, loosely defined as sludge.

- P1 represents the pollutants (composition and mass) in the facility's wastewater before any treatment.
- V1 is the volume of water containing these pollutants.

Because few data exist for P1 and V1, the equation at the bottom of Figure 2.6 displays an alternative way to discern P1 via examining national-level data on other flows. The figure and equation are color-coded, based on the EPA data sources reviewed in Table 2.5: green indicates data are available, orange signifies partial availability, and red specifies data are unnecessary.



$$P_1 = P_2 + P_3 = P_2 + (P_4 + P_5) + P_6$$

$$V_1 = V_2 + V_3 = V_2 + (V_4 + V_5) + V_6$$

Figure 2.6 Pollutant and discharge volume balance with data availability indicated

Based on the principles of a mass balance, P1 can be obtained by gathering data on

- P2 - facility effluent discharged directly to municipal treatment.
- P3 - facility effluent that continues to on-site wastewater treatment.
- P4 - effluent discharged as waste from on-site treatment.
- P5 - effluent discharged to municipal treatment after some on-site treatment.
- P6 - effluent discharged to a surface water body after on-site treatment.

The NPP data (partially P2 and P5) could not be used because, as discussed, this dataset is effectively unavailable publicly. Instead, the study employed DMR (P6) and TRI (partially P2 and P5) data in an effort to characterize the typical contaminants in wastewater discharges for each manufacturing subsector.

Assessing the representativeness of DMR data shows that overall, only 2.5% of the total establishments in the 2014 Manufacturing Energy Consumption Survey (MECS) were included in the 2016 DMR data.[17] This share varied widely by subsector: for example, 18.9% of MECS establishments in the petroleum and coal products subsector, 10.1% of establishments in the chemicals subsector, and 0.1% of establishments in the furniture and related products, printing, and apparel subsectors. For further details, refer to the supporting information S1 in Fuchs and Rao (2021).

EPA's Effluent Guidelines are national, technology-based, industry-specific standards governing wastewater discharges from industrial plants to surface waters and municipal wastewater treatment plants. Based on how treatment and control technologies perform, they are set to attain the greatest pollutant reductions economically achievable for each subsector (EPA 2018). EPA develops Effluent Guidelines without accounting for potential impacts of discharges on receiving water bodies—instead, the EPA addresses these impacts through water quality standards and water quality-based effluent limitations in individual facility permits. Many regard Effluent Guidelines as setting minimum technology-based standards for a subsector. Permitting authorities, typically individual states, set limits for water quality protection in part based upon these guidelines, with implementation through the NPDES Permit Program or the NPP. For more information on how the EPA formulates Effluent Guidelines, see Supporting Information S1 in Fuchs and Rao (2021).

Fuchs and Rao (2021) examined published Effluent Guidelines, hoping to learn more about typical contaminant concentrations by manufacturing subsector and understand which contaminants are historically difficult to treat. Table S1-1 in Fuchs and Rao (2021) displays tabular results by effluent guideline category, most recent revision year, NAICS subsector, facility types covered, wastewater streams, and significant regulated pollutants. This review demonstrates that the most recent revision year for any manufacturing subsector was 2005 (iron and steel manufacturing), and that Effluent Guidelines for 34 of 43 categories, or 79%, were completed more than 30 years ago. It is highly probable that some of these categories' manufacturing processes have significantly changed in the past three decades, especially in subsectors with rapid technological evolution. Effluent Guidelines drive coverage in EPA

[17] The MECS survey is administered every four years by the U.S. Department of Energy's Energy Information Administration and is a survey of the stock of manufacturing establishments in the U.S. and their energy use characteristics. The most recent survey data can be found here.

discharge permits; because the former are generally outdated, it is very unlikely that EPA data on which contaminants exist in manufacturing wastewater are comprehensive.

2.3.1.3 Conclusions

Blind spots exist regarding the characteristics of manufacturing water discharge, especially regarding contaminant mixes and flow rates or volumes of effluent. Desired data for the former include contaminant mixes for smaller manufacturing plants not required to have NPDES permits, as well as mixes in effluents sent to municipal wastewater treatment plants. For the latter, while several reviewed case studies contain process flows, data are needed regarding effluent discharges by disposal locations (e.g., to a municipal treatment plant or releases into surface waters). Because wastewater treatment research and technology development have primarily focused on municipal wastewater—with a small overlap with manufacturing wastewater constituents—models for sector, subsector, or regional analysis cannot currently be developed for industrial wastewater treatment technologies due to the absence of contaminant and flow data. Further, very few recent case studies include enough information even for individual analyses, in part because treatment processes are largely driven by the need to meet regulations. Against this backdrop of data scarcity for characterizing manufacturing discharge, the imperative for more resilience will increasingly make itself known as climate change stresses water supplies.

2.3.2 Wastewater Volumes

The EPA DMR provides the primary dataset for water volumes discharged by manufacturers. Only one state agency (North Carolina) collected discharge volumes and matched them with withdrawals, making it difficult to compare withdrawals and discharges at a facility level. There are two other major concerns about the DMR water volume data: (1) the DMR does not capture all facilities, and (2) the data quality is questionable. For the first, if a facility does not have a NPDES permit (due to small discharge volumes, not discharging to a U.S. waterway, or water sent to POTWs), it will not be reported in the DMR, impeding a full accounting of manufacturers' water use and discharge. The second concern recognizes that manufacturers often do not meter or monitor their discharge volumes. Without metering or monitoring, reported values are often based on estimates, utility bills, and/or discharge pump capacities (i.e., the value reported is the pump running at full capacity). Even with these concerns, the EPA DMR is likely the most comprehensive dataset for water discharge volumes.

The authors compiled discharge volumes from the 2017 EPA DMR for this analysis (EPA n.d.-a). In 2017, 11,017 facilities in the U.S. and Puerto Rico had a NPDES permit listed in the database. Of those, only 4,736 facilities reported a discharge volume above zero. This lack of discharge reporting could be explained by several reasons, including older, infrequently used permits for wastewater discharge, manufacturers meeting the permits' conditions and not reporting values, and the facilities discharging a *de minimis* amount of water that year. Of those facilities that reported, the manufacturing sector discharged 14,438 billion gallons (BG) for the year and had an average daily discharge of 37 BGD (see Table 2.6). In 2017, the top five industries (by 3-digit NAICS) discharging the most water were [325] chemical manufacturing, [324] petroleum and coal products manufacturing, [326] plastics and rubber manufacturing, [327] nonmetallic mineral product manufacturing, and [322] paper manufacturing.

Table 2.6 Average Daily Discharge and Total Annual Discharges by Manufacturing Subsector, from 2017 EPA DMR

Subsector [3-digit NAICS code]	Sum of average daily flow (million gallons per day [MGD])	Sum of total annual flow (MGD)
Food manufacturing [311]	3,430	1,414,262
Beverage and tobacco product manufacturing [312]	39	14,519
Textile mills [313]	273	100,671
Textile product mills [314]	20	7,533
Leather and allied product Manufacturing [316]	3	1,155
Wood product manufacturing [321]	572	208,678
Paper manufacturing [322]	4,205	1,544,363
Printing and related support activities [323]	17	6,113
Petroleum and coal products manufacturing [324]	6,024	2,575,864
Chemical manufacturing [325]	8,845	3,249,602
Plastics and rubber manufacturing [326]	5,539	2,018,906
Nonmetallic mineral product manufacturing [327]	4,767	1,740,522
Primary metal manufacturing [331]	948	350,781
Fabricated metal product manufacturing [332]	518	208,222
Machinery manufacturing [333]	165	60,139
Computer and electronic product manufacturing [334]	844	308,240
Electrical equipment, appliance, and component manufacturing [335]	9	3,573
Transportation equipment manufacturing [336]	1,687	623,451
Furniture and related product manufacturing [337]	2	559
Miscellaneous manufacturing [339]	3	994
Total	**37,909**	**14,438,146**

2.4 Facility-Level Data Collection Challenges

Based on past analyses and the present study findings, manufacturing water use data are unavailable in a form that can be used to answer the key questions laid out in Section 1.3. This section, much of which draws from McCall et al. (2021), proposes two levels of data that could be collected and made public: an “aspirational standard” and an “enabling standard.” It presents how each proposed level compares to the current level of data availability in terms of informing the questions posed in this section. The authors propose that the enabling standard would strike a balance between rigorously informing the four key questions and lessening the burdens on organizations making the data available.

The *aspirational standard* of water data is a time series dataset for individual facility water flows, as outlined in Figure 1.1. The number of data points collected at each facility would be determined by the number of sources of intake water, discharge locations, uses and quality of water (e.g., process water that requires treatment or non-contact cooling water), and presence of reused, recirculated, and recycled water flows. The data would be collected at a geographically diverse number of facilities and would be aggregated at the 6-digit NAICS designation with a high level of statistical confidence/certainty. The seasonality of water demands and availability would dictate the temporal frequency of data collection. This aspirational standard dataset would enable facility-level analysis and could be aggregated in many ways (e.g., across processes, by region/watershed, or by subsector). Because the data would be collected at the facility level, impacts across the most granular watershed or political boundary disaggregation (i.e., HUC-12 or towns) would be possible.

However, the collection and sharing of this type of data would require considerable effort by policymakers to enact policies that would coordinate data reporting and the facilities that must produce and share the data. Such policies likely would present competition concerns among manufacturers and require collecting, scrubbing, and anonymizing the data. Further, the current lack of water monitoring at industrial facilities presents challenges from both a sensor and monitoring perspective and from a data sharing and regulatory perspective. Cybersecurity concerns for such a data-intensive critical infrastructure system must also be considered and addressed. When water flow and quality submetering is more readily deployed, this aspirational standard dataset may become more tenable. However, it will likely be infeasible for the foreseeable future based on the paucity of submetering and the current availability of data. Advances in metering, metering standards, digital twin analysis methods, and cybersecurity may enable the development of these data sources, but this dataset likely represents the future of data collection. Some facilities and companies may choose to adopt these metering standards, but likely not until midcentury or later (2050s) will it be common in industry without enabling technologies.

In the interim, the *enabling standard* represents a midpoint between the current data and the aspirational standard, providing a touchstone dataset that researchers, policymakers, and technology developers could use to inform R&D. Under this standard, a statistical sample of facility-level water use data is collected from across manufacturing subsectors (that are at a minimum aligned with the NAICS 3-digit disaggregation). The enabling standard includes water withdrawal and discharge information as well as water use characteristics of key processes and facility equipment (e.g., boilers, clean-in-place, and cooling towers). The enabling standard resembles the current national-level Canadian IWS and MECS, which has served as a cornerstone for energy analysis. One such set of analyses is the DOE's Energy Bandwidth Studies,[18] which details the subsector-wide energy savings potential from the adopting emerging technologies. Such analysis, if done for water, would directly inform what process improvements are available or needed to reduce water demand (Q3). Sampling and collection methods from IWS and MECS would likely form the foundation for developing and implementing the enabling standard dataset. Table 2.7 compares the data qualities, benefits,

[18] Available at https://www.energy.gov/eere/iedo/manufacturing-energy-bandwidth-studies

and drawbacks of current data and both proposed data standards.

Table 2.7 Comparison of Dataset Data Quality Considerations, Benefits, and Drawbacks

Dataset type	Data quality considerations	Benefits of dataset type	Drawbacks of dataset type
Current data: quinquennial (every five years) data survey, water use coefficients, disaggregated state-level data	• No consistent subsector identifier • Aggregated over county/state level • Aggregated with other uses (i.e., construction) • Limited facility-level data • No process-level data • Data updated every 5 years • Relies on 1980s era water coefficients • Unlinked withdrawal & discharge data • Annual data	• "Status quo" • Currently available • Enables macro-level analysis • Reports which data are being monitored by manufacturers	• Insufficient granularity for modeling • Not updated with enough frequency • Does not allow for facility-level analysis • Leads to wide variance in water-use coefficients • No industry-specific or process-level distinctions
Aspirational standard: real-time, facility-level water data broken out by process	• Facility-level water use & discharge, both quality & quantity • Process-level information within facility • Facility identification at 6-digit NAICS level • Time series data; interannual data • HUC-12 watershed information	• Enables location-specific risk assessment • Allows for watershed & climatic change modeling • Ease of environmental, social, & governance reporting	• Competition and privacy concerns • High accuracy required for high granularity • Significant effort & cost to manufacturers • Manufacturers unlikely to have these data currently
Enabling standard: touchstone dataset with enough information to inform policy making & economic decisions	• Linked withdrawal & discharge coefficients • Minimum 3-digit NAICS identifiers • Aggregated facilities at watershed level (HUC-8) • High-level process information (cooling vs. sanitary vs. manufacturing) • Data updates every 1–2 years • Data reported annually	• Enables an industrial water use bandwidth study • Provides touchstone dataset for regression analyses • Avoids large collection efforts required by the aspirational standard • Linked withdrawals, discharges, & consumption for watershed • Ability to perform impact, risk, & water efficiency analyses • Informs industrial water R&D	• Policy measures likely needed for survey or data collection • Cost to manufacturers for metering upgrades

Addressing the data gaps identified in Sections 2.1 and 2.2 will require the missing information to be available and collected at the facility level. Note that some of this data may be available at the individual facilities and not reported or only reported to entities (i.e., insurance providers) where the data is private—underlining the need for more publicly available sources. Collecting this information would primarily require the installation of meters or estimation techniques in lieu of meters. However, gathering this information is difficult at many industrial facilities and can be expensive to incorporate. This section describes some of these difficulties based on experiences utilizing DOE's open-access Plant Water Profiler (PWP) tool (DOE 2021). The PWP tool is based on a water mass balance analysis and is the main analysis tool for plant water use assessments, Water In-Plant Trainings (INPLT), that occur as part of DOE's Better Plants program. Three pilot water INPLTs were conducted in 2019 at three facilities manufacturing iron and steel, fiberglass, and vinyl siding, respectively. (For more detail on findings from these pilot studies, see Section 4.3) Importantly, these three water INPLTs revealed challenges pervasive in many manufacturing facilities, such as the quantification of uncontrolled or unmetered water flows.

One of the challenges that facilities face is the capital cost associated with purchasing and installing submetering. The Better Plants INPLT program provides facilities with technical assistance and portable equipment for measuring water use at the subsystem level and conducting an accurate water mass balance to detect unintended losses or inefficient uses of water. The use of portable flow meters for unintrusive spot measurement has helped facilities characterize their water use by subsystem and detect unintended losses or rainfall infiltration issues. One common challenge in providing facility assistance was the placement of the portable flow meters. Strap-on ultrasonic flow meters have the advantage of providing accurate readings under the right conditions. One of the main requirements is that the meter should be placed at a distance 20 to 25 times the pipe diameter from any pipe fittings (e.g., bends, elbows, valves, connectors). At some facilities it has been challenging to find straight sections of pipe long enough to reduce the effect of disturbances.

Once the facility has collected measurements on individual systems or processes, it can proceed to estimate a water mass balance. One of the main challenges at this stage is the lack of metering of self-supplied water sources. Some facilities rely on billed municipal water distribution as well as self-supplied water from streams and groundwater wells. The self-supplied water sources are not always metered. When this is the case, the water use of processes and equipment can be estimated to approximate the mass balance, but this approach does not depict all flows accurately.

In addition, several processes in facilities may use water volumes controlled by the operator in charge. Processes like open spraying are usually behavior-driven and vary significantly between shifts. These water volumes are difficult to estimate without proper controls. In these cases, facilities may opt for providing an average volume of water, but this may not accurately reflect inefficient water uses. The lack of metered volumes impedes facilities from implementing corrective actions to optimize water use.

Without proper characterization of water inflows into the facility and accurate water flows associated with specific processes or equipment, routing flows through the facility until the final discharge becomes difficult. Some processes and systems within facilities tend to drain the water by gravity into underground channels that are hard to access. These channels typically drain to the facility outlet, adding complexity to estimating the water mass balance. Moreover, unintended water infiltration and inflow derived from wet weather conditions and cracks in underground pipes can add another layer of complexity to reconciling the water mass balance.

With all the potential variability in water use in industrial processes, facilities are encouraged to continuously submeter water flows for all their processes, especially for water-intense processes, as well as track all the water inflows by source and water quality. The installation of flow meters and proper characterization of system-level flows need an initial investment and may seem unattractive to facilities because it does not directly translate into water, energy, or cost savings. However, the control and optimization of flows can reveal hotspots that require attention, inefficiencies in water use that require corrective action, modifications in the system that can optimize the use, reuse, recirculation, and recycling of water. Therefore the investment can indirectly lead to water, energy, and/or cost savings.

2.5 Exemplary Risk Analysis

Rectifying the data issues established in Section 2.4 will support the thorough evaluation and identification of water-related risks facing the manufacturing sector, potential mitigation strategies, and related R&D needs. Sections 2.5.1 and 2.5.2 describe two such analyses that identify physical and thermal water risks facing U.S. manufacturers. At the current level of data availability, both analyses support a broad understanding of the magnitude and implications of the risks. However, more comprehensive data will allow for targeted regional, subsector (and even facility), and temporal analysis to precisely identify when and where these risks are greatest.

2.5.1 Manufacturing Subsectors at Physical Risk

As reviewed in Section 1.4, water risks brought about by physical scarcity represent an omnipresent threat in the U.S. that will be exacerbated by climate change. For manufacturers relying on these waters, physical water shortages can lead to higher costs for purchased water, increased scrutiny of their self-supplied water use, disruptions to water services, and the curtailment of production, among other impacts. This section highlights key results from a separate recently published analysis conducted by some authors of this report on the manufacturing subsectors most at risk of physical water shortages. (For the full analysis, including details on the methodology and data sources, see Rao, Sholes, and Cresko [2019], publicly available here).

There are numerous metrics for calculating water stress (Brown and Matlock 2011; Damkjaer and Taylor 2017). One such index is the Water Supply Stress Index (WaSSI), which is a ratio of a watershed's rate of anthropogenic water demand over the rate of natural water replenishment (Sun et al. 2008). It is represented as:

$$WaSSI = \frac{Water\ Demand + Water\ System\ Loss}{Surface\ Water\ Supply + Groundwater\ Supply + Return\ Flows}$$

Equation 2

A WaSSI of 1 means that there is more anthropogenic water demand than natural water replenishment in a watershed. Note that the WaSSI excludes environmental/ecosystem water needs (e.g., fish, plants, and wildlife). Therefore, a WaSSI of 1 is well past the demarcation of water scarcity based on natural water availability. This does not mean that engineered systems cannot bring additional water to the watershed, but these systems would remove water from the source watershed artificially and impact water availability in the source watershed.

Using data from the WaSSI Ecosystems Services Model (NCSU, USDA, and USFS n.d.), the authors calculated the WaSSI for all watersheds at the HUC-8 designation for the period between 1985 and 2010. The HUC-8 designation subdivides the U.S. into 2,264 divisions and aligns best with the number of counties in the U.S. (3,142). (Refer to Rao, Sholes, and Cresko [2019] for more details on how watersheds were mapped to counties for this analysis.) Eighty-five of the counties in the U.S. (2.7%) had a WaSSI greater than 1.

Comparing the counties with a WaSSI over 1 to the manufacturing subsectors drawing water from these counties yields a list of manufacturing subsectors with the greatest risk of experiencing physical water shortages. The ranking of subsectors by their percent of withdrawal from counties with a WaSSI greater than or equal to 1 is shown in Table 2.8.

Table 2.8 Percent Share of Water Withdrawals from U.S. Counties With a Long-term WaSSI > 1 for Each Manufacturing Subsector, for the Period from 1985–2010

Subsector and NAICS code	Percent of water intake in counties with WaSSI > 1
Primary metals [331]	35
Fabricated metal products [332]	10
Transportation equipment [336]	10
Petroleum and coal products [324]	9
Plastics and rubber products [326]	9
Nonmetallic mineral products [327]	8
Machinery [333]	8
Food [311]	7
Computer and electronic product [334]	7
Beverage and tobacco products [312]	6
Paper [322]	6
Electrical equipment [335]	5
Textile product mills [314]	3
Chemicals [325]	3
Textile mills [313]	2
Wood products [321]	2
Other [315, 316, 323, 337, 339]	8

Notably, 35% of water withdrawals for the primary metals subsector is from counties with WaSSI > 1. An examination of the water withdrawals by county for the primary metals subsector (Figure 2.7) shows a large concentration of water withdrawals around the Great Lakes, specifically Lake County, IN, with a WaSSI of 1.7.

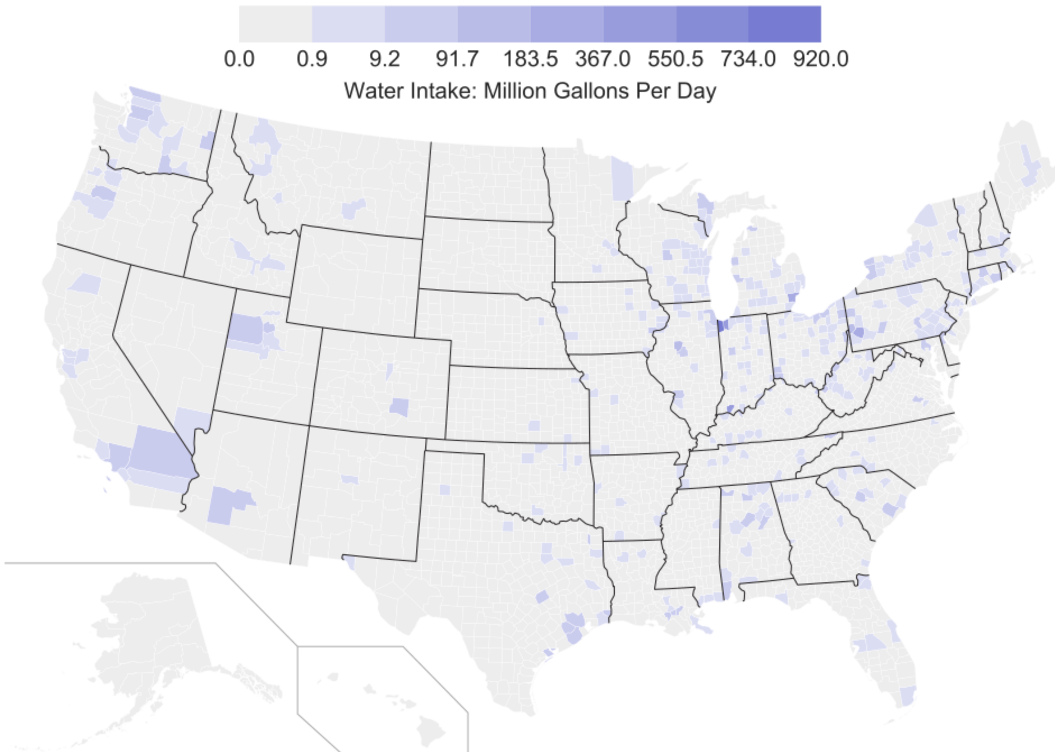


Figure 2.7 Water withdrawals by county for the primary metals subsector
Figure source: Rao et al. 2017

2.5.2 Manufacturing Subsectors at Thermal Risk

This report examines water-related risks for manufacturers, many of which are physical in nature. In addition to physical risks, thermal risks related to water will also increase in a warming world. The thermoelectric power generation sector, which requires significant volumes of water for cooling, has already experienced reduced thermal efficiency, regulatory conflict, lower load, and even disruptive shutdowns (Förster and Lilliestam 2010; Madden, Lewis, and Davis 2013; van Vliet et al. 2016). Such risks may also concern manufacturing plants, which this subsection assesses via an example analysis.

The effects of climate change-induced warming of surface waters on the manufacturing facilities utilizing the surface water as a heat sink is a water supply risk that, to date, has not been examined. Manufacturing facilities use surface water for various purposes, including on-site power generation and process cooling. For power generation, the temperature of the cooling water directly affects the energy efficiency of the system and the magnitude of energy generated, given the principles dictating Carnot efficiency. Typically, warmer waters lead to reduced energy-generating capacity. If current trends of warming surface waters continue, manufacturers will experience reductions in the capacity of cooling systems that support existing on-site power-generation systems, compromising reliability. This will, in turn, lead to disruptions in electricity supply at a manufacturing facility and/or the need to acquire additional generation capacity or purchase electricity from the grid.

Such occurrences have been documented in the power generation sector. McCall et al. (2016) identify 22 incidents between 2000 and 2015 where power-generating facilities in the U.S. were affected by high surface water temperatures and water flow shortages. Looking into the future, Miara et al. (2017) estimate that the mean adjusted available capacity of power plants in the

U.S. will decrease by 2.4% on average by the 2040s under scenarios of continued climate change. Given the common use of Carnot cycles, one should anticipate similar occurrences at manufacturing facilities.

This section investigates the water and energy impacts of elevated surface freshwater temperatures on the sensible cooling capacity of manufacturing operations using these waters as a heat sink. *Sensible cooling capacity* refers to the amount of cooling capacity available without changing the phase of the cooling medium (in this case, water). The analysis focuses on *once-through cooling* (systems that pass water over heat exchangers to cool a process load, such as condensers for a power-generating system, and directly discharge the water back to its source). *Closed-loop* (recirculating) cooling systems are too complex to accurately model for this analysis. However, the formulations and concepts analyzed are applicable wherever water is used as a heat sink. In instances where existing cooling capacity is limited by warmer surface freshwater temperatures, the analysis quantifies additional energy consumption from alternative technologies that minimize burden by using less water.

As described in this report, current and publicly accessible data on manufacturing water use is not available. Past information shows 48.1% and 44.8% of U.S. manufacturing water intake was for "other cooling and condensing" in 1973 and 1978, respectively (Becker 2016).[19] While this information has not been collected recently in the U.S., Canadian government surveys show that 45% of Canada's manufacturing water intake is for cooling, condensing, and steam (Cameron et al. 2014). Given similarities in geography and economies between the U.S. and Canada[20] and the previous data points for U.S. manufacturers, it stands to reason that a significant portion of U.S. manufacturing water intake is for cooling.

Ample evidence suggests that surface water temperatures in the U.S. are rising (Kaushal et al. 2010; Sahoo et al. 2011; Isaak et al. 2012). Kaushal et al. (2010) found that major rivers and streams in the U.S. experienced significant increases in water temperatures over the past decades, with a water temperature rise between 0.009°C per year (Hudson River at Poughkeepsie, NY between 1908 and 2006) and 0.077°C per year (Delaware River at Chester, PA between 1965 and 2007). These increases are predominantly due to increasing air temperatures (from climate change along with more impervious surfaces and urbanization), while waste heat discharges from power plants and industrial facilities also contribute. In the absence of sufficient action to curb climate change and its impacts on surface water temperatures, it can be expected that surface waters will continue to get warmer. One study estimates that the mean temperature for the years 2071–2100 in various river basins in the U.S. is expected to increase by 1.1°C–2.4°C relative to average 1971–2000 values (van Vliet 2013). Studies predict that some regions will experience more warming than others. For example, Chandler et al. (2016) found that the 30-year average of mean August river temperatures for the 2030–2059 time period for western U.S. water systems will increase by 0.8°C–1.5°C compared to the historical average between 1995–2009. Meanwhile, Walker, Letcher, and Hocking (2020) used RCP 4.5 and 8.5 and found that the average of mean August river water temperatures in the Northeast and Mid-Atlantic between 2036–2055 will increase by 1.2°C–1.5°C compared to the historical average between 1995 and 2009 (Walker, Letcher and Hocking 2020; Karmalkar and Bradley 2017).[21] Further, Cheng et al. (2020), under the RCP 8.5

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[19] Steam electricity generation accounted for 18.1% and 15.8% of water intake by U.S. manufacturing in 1973 and 1978, respectively.
[20] Both are G8 countries with a similar share of GDP attributable to manufacturing (10% in Canada in 2016 and 11% in the U.S. in 2018, per the World Bank).
[21] RCP 4.5 represents a future where the radiative forcing from the atmosphere is stabilized at 4.5 W/m^2 by 2100. RCP 8.5 represents a future where radiative forcing reaches 8.5 W/m^2 by 2100 and continues to increase thereafter.

scenario, estimated that the 30-year average of mean August river temperatures in the Southeastern U.S. for the 2070-2099 period will rise by 2.4°C–4.7°C compared to historical averages between 1995 and 2009.[22] This regional variation, with the Southeast subject to the greatest warming, aligns with similar findings from other studies (van Vliet et al*.* 2012).

To evaluate the impacts of increased surface water temperatures on the sensible cooling capacity of once-through cooling processes at manufacturing plants, a term is developed and called the loss in sensible cooling factor (LSCF) is defined as shown below:

$$\delta/(T_{out,ref} - T_{in,ref})$$

Equation 3

where,

> δ = change in the surface water temperature
>
> $T_{out,ref}$ = the exiting water temperature of the cooling operation at a reference condition through outfall pipes
>
> $T_{in,ref}$ = the entering water temperature of the cooling operation, taken as the surface water temperature at a reference condition

Note that the LSCF is only applicable to sensible cooling and not applicable to systems that rely on latent heat transfer. Further, the temperature at the outfall pipe may differ from the temperature at the condenser outlet. When condenser outlet water is transported through pipes to the external outfall pipes, it will lose a portion of its thermal energy. However, due to the lack of specific data on the size and length of the pipes, the temperature of spent cooling water at outfall pipes is assumed identical to the temperature at condenser outlet.

The analysis applied the LSCF to a curated dataset to evaluate the increased energy impacts needed to overcome increased cooling surface water temperatures. Combining EPA data on cooling water intake volumes and outlet temperatures with published estimates for surface water temperatures, intake flow, intake temperature ($T_{in,ref}$), and outlet temperature ($T_{out,ref}$), datasets were compiled for 33 facilities. These 33 facilities primarily rely on once-through cooling systems. To maintain consistency and reduce uncertainty attributable to methodological differences used in the literature, projections for surface water temperatures were not used directly in this analysis. Rather, the historical surface water temperature was obtained from these models and increased by 0.5°C, 1.0°C, 2.0°C, and 3.0°C (δ) to analyze several future scenarios.

In these future scenarios, it was assumed that the outlet temperature ($T_{out,ref}$) remains the same as the historical values. The EPA enforces Section 316(a) of the U.S. Clean Water Act, which regulates the discharge of heat from industrial sites into surface waters (eCFR Title 40 Chapter I Subpart D §125.70). Generally, surface water temperatures near the facility discharge outlets (for example, outfall pipes) are not to exceed 32°C, although regional authorities (mostly states, but sometimes multi-state EPA regions) are allowed to establish their own limits (Liu et al*.* 2017). Regional authorities can also set limits on the rise in surface water temperature that can occur from thermal discharge into surface waters. Most states limit temperature rise to 2.5°C–3°C (Liu et al*.* 2017). Based on the available data for the manufacturing facilities in this analysis, values of $T_{out,ref}$ are below the maximum temperature in freshwater streams allowed

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[22] The study area in Cheng et al*. (*2020) includes parts of Indiana and Ohio (see **Error! Reference source not found.**). Here, these states are included whenever "Southeastern U.S." is discussed in this section, even though they are not Southeastern states in the general sense of the word, in order to be consistent with Cheng et al.'s (2020) description of the study area.

per the EPA's thermal effluent regulations (Liu et al. 2017). But the values for $T_{out,ref}$ do come close to the threshold temperature values for a few days of the year for some manufacturing facilities. Based on this, it is assumed that the manufacturing facilities would want the future $T_{out,ref}$ to be the same as the historical values to avoid the risk of regulatory penalties, disruption to their operations, and degradation of the surrounding water ecosystem. It is important to note that Section 316(a) regulates the temperature rise in the surface water body, but the permits established to meet this regulation regulate the water temperature at the outfall pipe. So, while the facility may be able to increase the temperature at the outfall (provided it still adheres to the existing permit), it would be counter to the intent of Section 316(a).

The locations of the 33 manufacturing facilities in this analysis are shown as green dots in Figure 2.8. They are located in 21 states, with five facilities in Washington; 4 in Ohio; two each in Indiana, Kentucky, Oregon, New York, and Pennsylvania; and one each in Alabama, Colorado, Connecticut, Georgia, Maine, Massachusetts, Mississippi, Montana, New Jersey, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia. Individual facilities are designated by the two-letter state abbreviation in combination with a number if more than one facility is present in a state (e.g., WA5 denotes the fifth facility in Washington state). The region enclosed by the purple line on the left is the study area of Chandler et al. (2016). The region enclosed by the red line in the northeast is the study area of Walker, Letcher, and Hocking (2020), and the region surrounded by blue is the study area of Cheng et al. (2020). For facilities included in both Walker, Letcher, and Hocking (2020) and Cheng et al. (2020), data from the latter was used because of its comprehensive water temperature modeling procedures.

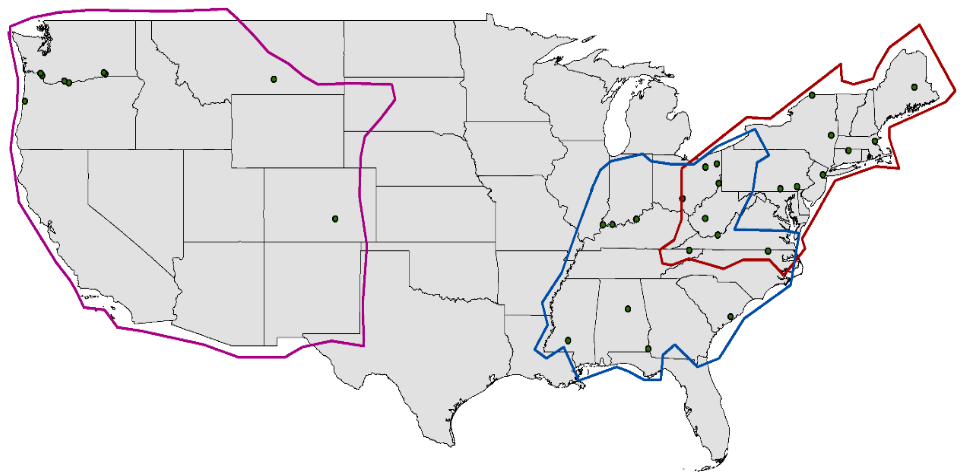

Figure 2.8 Manufacturing facilities included in analysis, as well as regional study areas

Table 2.9 shows the subsectors to which the 33 facilities belong. Seven of the 21 manufacturing subsectors, as classified at the 3-digit NAICS level, are represented in the 33 facilities selected for this analysis. Table 2.9 also compares the distribution of the selected facilities by subsector to the distribution of all manufacturing facilities that reported cooling water intake to EPA (those using more than 2 MGD of surface water for cooling) and the EIA's MECS data. To better understand the representativeness of the 33 facilities examined here, an additional comparison is made to the estimated percent of overall U.S. manufacturing sector water intake for each of the subsectors represented by the 33 facilities (Rao et al. 2017). These comparisons are made. In general, the subsectors to which the facilities examined belong do not represent a significant portion of all manufacturing facilities. However, they do constitute a significant share of overall U.S. manufacturing water intake (the seven subsectors represented constitute nearly 90% of all manufacturing water intake).

Table 2.9 Distribution of 33 Manufacturing Facilities in This Analysis

Subsector	Distribution of facilities included in analysis (n=33)	Distribution of facilities in the EPA data (n=196)	Distribution of facilities per MECS (n=175,107)	Estimated % of overall U.S. manufacturing water intake
Chemicals manufacturing	27%	21%	5%	21%
Paper manufacturing	36%	39%	2%	29%
Petroleum and coal products manufacturing	6%	22%	1%	13%
Primary metals manufacturing	21%	8%	2%	26%
Textile mills	3%	1%	1%	<1%
Transportation equipment manufacturing	3%	1%	4%	<1%
Wood product manufacturing	3%	1%	5%	1%

Figure 2.9 shows the LSCF values for 5 of the 33 facilities examined. These LSCF values are for increases in surface water temperature (δ) of 0.5°C, 1°C, 2°C, and 3°C. The 5 facilities represent the minimum (WA5), 25th percentile (OH4), 50th percentile (OR2), 75th percentile (NY1), and maximum (NJ) LSCF of the 33 facilities examined. In effect, each line represents LSCF values for a specific $T_{out,ref} - T_{in,ref}$ (ΔT_{ref}). The LSCF is larger for smaller ΔT_{ref}. Essentially, a given (δ) will represent a larger share of the existing sensible cooling capacity for facilities with a smaller ΔT_{ref} compared to those with a larger ΔT_{ref}. For the facilities evaluated, a 0.5°C increase in surface water temperatures would lead to a 2%–12% reduction in cooling capacity. A 3°C increase would lead to a 15%–72% reduction in cooling capacity.

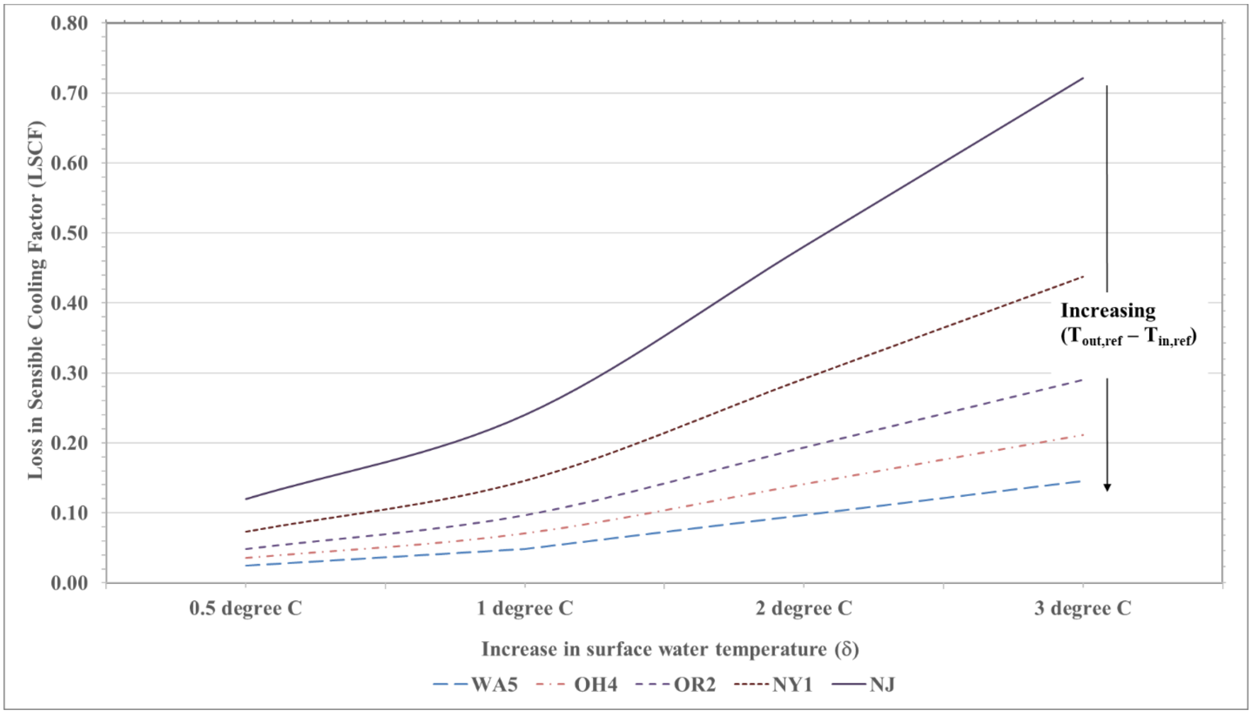

Figure 2.9 The LSCF for 5 of the 33 facilities examined as a function of increases in surface water temperatures

If the surface water temperature rises due to the deleterious effects of climate change, it is beneficial to the environment when facilities reduce the existing amount of discharged water. In other words, when the ambient surface water temperature increases, reducing the amount of discharged heat will prevent further deterioration to the ecosystem. While a facility could potentially increase the flow rate of cooling water to limit its temperature gain, it may be techno-economically impractical to upsize existing pumps, piping, and condensers to do so; further, obtaining updated permits for higher cooling water intake may also be complicated. With that in mind, facilities may find it more feasible to utilize alternative technologies, such as dry cooling systems that utilize relatively less water (or none at all) to satiate the lost thermal energy.

If dry cooling systems (e.g., industrial-scale air-cooled condensers) are utilized, there will be an increase in energy consumption at the facility attributable to running the system. Using the data compiled for the 33 facilities, the analysis examined the increase in energy consumption associated with replacing the lost cooling capacity with air-cooled condensers. For the analysis, a typical fan power draw of 0.03 kW per ton of cooling was used (Maulbetsch 2002).[23] Table 2.10 shows the results for the facilities with the minimum (NY1), 50th percentile (NC), and maximum (IN2) increase in energy consumption of the 33 facilities examined. The increased energy consumption is a function of the mass flow rate of cooling water, its temperature, and δ being evaluated. At the most extreme case evaluated, an additional 12,160 kilowatt-hour (kWh)/day would be required to run dry coolers to offset the LSCF (IN2). These impacts could

[23] The amount of fan power drawn per ton of cooling provided by the air-cooled condenser varies based on various factors like the ambient temperature, condensing temperature, fan efficiency, and other variables. The power draw values from the literature ranged from 0.03 kW to 0.08 kW per ton of condenser load. This analysis used a conservative estimate of 0.03kW/ton.

be significant if extrapolated to other manufacturing facilities in the country that currently rely on once-through cooling systems and water from surface water sources for their cooling needs. Relating this data analysis to the EPA rulemaking on cooling water intakes shows that almost 60% of the manufacturing facilities with large surface water withdrawals could be using once-through cooling systems (EPA n.d.-b).

Table 2.10 Increased Energy Consumption Associated with Utilization of Dry Cooling Technologies with an Efficiency of 0.03 kW/ton to Compensate for LSCF for 3 of 33 Facilities Evaluated

Facility	Mass flow rate of cooling water intake (MGD)[24]	δ (ºC)	LSCF	Dry cooling energy consumption (kWh/day)
NY1	0.7	0.5	0.07	13
	0.7	3.0	0.44	76
NC	5.5	0.5	0.06	103
	5.5	3.0	0.37	617
IN2	108.1	0.5	0.03	2,027
	108.1	3.0	0.16	12,160

Dry cooling technologies are not the only option for supplementing once-through cooling. Wet cooling recirculation or hybrid systems can replace once-through cooling systems. However, each system type (once-through cooling, dry cooling, and wet cooling recirculation or hybrid systems) has drawbacks (EPRI 2012b; EPA Office of Water 2014). For instance, the capital cost of installing dry cooling systems is 3.5–4 times that of wet cooling systems (Maulbetsch 2004). Wet cooling recirculating systems transfer the heat to the surrounding air through evaporation, and the cooled water is used again at the facility, thereby reducing the amount of water withdrawn. Van Vliet et al*.* (2016) state that recirculating cooling systems result in lower water withdrawals and make power plants less vulnerable to rising river water temperatures. However, due to their reliance on latent cooling, these systems lead to increases in consumptive water use (water that is used and not returned to the same watershed), exacerbating any physical water scarcity issues. Further, recirculating systems require chemical additives to treat and disinfect the water. Often, these are hazardous chemicals that require safe handling. Hybrid cooling systems that combine wet and dry systems are another technology option. Integrated controls that can modulate between the dry and wet cooling systems, depending on water and other environmental conditions, could minimize the additional energy requirements (EPRI 2012a). Because these types of systems are considered an emerging technology, they could be perceived as a technological risk. The use of diffuser systems that dilute the hot effluent water that is discharged into surface water bodies is another way to reduce the temperature rise in those water bodies (Roberts 2011).

The development and use of technologies like thermal storage (that can shift the thermal loads of power plants and take advantage of cooler nighttime and seasonal ambient temperature) in conjunction with technologies that can use absorption cooling and radiative heat transfer to the local environment can also lessen the impacts of surface water temperature rise at manufacturing facilities (Stark and Klausner 2017). Another option is for the facility to find a

[24] 1 MGD is equivalent to 3,785 m^3/day.

source of cooler water, perhaps through relocating intake to a cooler portion of the water source. The presence of cooler waters will be highly site-specific. Regardless, relocating intake structures will require very high capital costs and may require revising water permits (EPA Office of Water 2014). As a result, this option is more feasible for newly constructed facilities.

Considering the disadvantages (or pre-commercial developmental state) of these other technologies and options, perhaps the best option for minimizing water impacts from once-through cooling operations supporting on-site power generation is the adoption of water-free renewable electricity generation systems such as solar photovoltaics or wind to replace conventional power generation. Studies have shown that these renewable systems have very minimal water use requirements during their use phase (Averyt et al. 2011).

3. Risk-Informed Water Valuation to Guide Technological Innovation

Section 3 Summary

- The manufacturing industry has often considered water too cheap to conserve. Because the price of water is negligible relative to total manufacturing costs, it is difficult to justify implementing water conservation technologies for financial reasons alone.
- The full value of water to manufacturers far exceeds the price of water: it includes additional in-plant treatment and energy costs, as well as economic and social costs related to scarcity and environmental externalities. Section 3 summarizes recent literature on water valuation metrics.
- Better data transparency has led some large manufacturers to champion water sustainability via supply chain sustainability initiatives, environmental profit-and-loss accounting, estimating risk-adjusted values of water, hydro-economic modeling, natural capital asset valuation, and developing value chain indices.
- If adopted, such fuller water valuations can help make the business case for developing and deploying cost-effective water-conserving technologies, thereby improving the sustainability of the manufacturing sector with respect to water.
- Much of Section 3 draws on the following work published by report authors: Das et al. (2023).

3.1 Introduction

Water is a critical component of many manufacturing processes, and its uninterrupted supply is essential to many manufacturing operations. Aside from manufacturing process operations, water is used for purposes like cooling, power generation, sanitation, and fire protection. Often, these uses are essential to operations. For example, without water for cooling and an alternate heat sink, process equipment can overheat, fail, and cause a plant to shut down. Consequently, water demand and its subsequent value become critical issues when managing or mitigating water-related risk events or shocks (e.g., price, availability, and quality). These water shocks could occur due to a lack of reliable water supply, potentially driving higher temporary regional water prices. Unlike other commercial commodities, the price paid for water does not fully reflect the value it provides to the consumer (Black & Veatch 2016; Hukka and Katko 2015). As a result, this underpriced resource is not optimally utilized, and significant operational inefficiencies occur. The mismatch between price and value inhibits developing and deploying water-saving technologies, as the return on investment is calculated using price, not value. Further, the low price of water often means that capital improvements to increase the utilization efficiency of other resources with higher operational costs (e.g., electricity) rate a higher priority to manufacturers (Seneviratne 2007; Oppenheimer et al. 2016; Moore and Buzby 2017). The authors adapted the work in this section from a recent peer-reviewed article in *Water Resources and Industry* by Das et al. (2023), who argue that reframing the price of water to better incorporate value would help advance the state of water-saving technologies.

Water cost and price (e.g., utility tariff) are the two commonly used metrics to understand the economic impacts of either industrial self-supply withdrawals or utility water use. In economic terms, *cost* represents the expenditures incurred to produce a certain good, while *price* is defined as the rate at which one exchanges money for a good. *Market prices* demonstrate the relation between *supply* (what is produced, and at what cost) and *demand* (the value to buyers), and appropriate pricing mediates between the full costs of production and the demand for the resource. However, water prices often do not even cover the direct costs of supply, let alone the full value of water (including opportunity and externality costs), precluding the efficient and sustainable use of water (Rogers, de Silva, and Bhatia 2002; Gohil and Méndez Vives 2016). The share of water cost relative to total manufacturing cost is significantly small (< 3%) (Rojas 2005; Schellekens et al. 2018), driven mainly by low utility tariffs and self-supplied sourcing (i.e., no volumetric water or connection costs) without consideration of additional necessary in-plant costs. U.S. industrial water tariffs vary widely over space and time in the range of ~1 to 3 $/kgal per month (~0.26 to 0.79 $/m^3) (Beecher and Kalmbach 2013; Black & Veatch 2013). Moreover, three-quarters of U.S. manufacturing water intake stems from self-supplied sources, as shown in Figure 2.1 (Section 2.1) (Rao, McKane, and Fontaine 2015).

Water is a highly location-specific resource, meaning localized water stress is a risk factor for manufacturing operations nearby (Gohil and Méndez Vives 2016). To date, abundant domestic water supply has caused only limited supply-risk impacts in specific regions such as California and the Southwest. Further, property taxes and local bonds often make up the difference between the production and delivery cost to utilities and the tariff paid by consumers. When utilities are still unable to cover their costs, they delay maintenance and investments, resulting in failing water infrastructure and negatively impacting water quality and reliability of supply. For example, disruptions to water service in 2019 represented economic losses of $51B for the 11 industries most reliant on water, including manufacturing (ASCE 2020). Because current tools to assess water risks do not fully account for the economic value of water to individual businesses or other stakeholders, manufacturers are likely to misunderstand or undervalue water risks, particularly in highly developed river basins (Reddy et al. 2015).

However, water supply disruptions are projected to increase with aging/failing water infrastructure, changing environmental water discharge regulations, and more drought and extreme weather due to climate change impacts. The full value of water to manufacturers should encompass the risks of water shortages or poor water quality that could lead to the disruption of production. Appropriate water valuation is important to quantify these external and indirect water supply disruption impacts and is critical for assessing the potential of cost-effective industrial water conservation technology opportunities. In addition, water valuation would enable individual manufacturers to better understand tradeoffs related to water use, for example, when inputs and outputs are stated in financial (e.g., dollar) terms. Water valuation would also benefit local utilities' ability to efficiently allocate water resources. More comprehensive economic evaluation methods specific to the manufacturing sector are necessary to facilitate developing and deploying water savings technologies in industry.

Section 3 seeks to establish a framework for improving the valuation of water to support decision-making processes impacting the sustainable use of water in the manufacturing sector.

Based on findings from the literature, it identifies and recommends the considerations necessary to appropriately value water as a resource, focusing on upstream and downstream impacts to the facility and the ecosystem within which it operates. Next, metrics used in the literature for understanding the value of water are compiled and reviewed. Finally, the section summarizes findings from case studies of industrial facilities using a more comprehensive valuation of water.

3.2 Water Valuation Concepts: Cost, Price, and Value

The price of a typical commodity is conditioned on its quantity. Water is a nonstandard commodity, meaning it possesses special attributes beyond quantity with no market pricing impacts (Chong and Sunding 2006). Special water attributes include the following (Black & Veatch 2013; Young 2005a):

- Water is mobile (flows instead of stocks) but challenging and expensive to transport across large distances/elevations, making it difficult to establish property rights and to dispatch it where needed.
- Freshwater availability varies across space and time due to weather/climate.
- Water quality matters for specific applications.
- Water performs multiple social functions calling for regulated pricing.
- Water has associated externalities due to high interdependencies among users.
- There is a natural monopoly where cost is mainly driven by the amount and type of supply source.
- Water can have high variability of demand.
- Public regulation is challenging due to numerous decision-makers at various levels.

In some regions, organizations are creating innovative ways to price these attributes. For example, farmers, hedge funds, and municipalities alike can hedge against—or bet on—future water availability in California, the biggest U.S. agriculture market and the world's fifth-largest economy (Chipman 2020). Ideally, for sustainable use of water, price and value should balance each other (Rogers, Bhatia, and Huber 1998).

Due to the many critical social functions that water performs, primarily government authorities regulate the price and allocation of water. The price depends on the set utility tariff in that given region. From the utility perspective, efficient price signals would help promote water conservation, justify expenditures on water-saving technologies, and help collect sufficient revenue for daily operation and maintenance of the water delivery system and future infrastructure investments (Black & Veatch 2013; CMAP, IISG, and University of Illinois Extension 2012). However, bills for purchased water or wastewater treatment may obscure overall costs, given the high variation of billing across utilities and the inclusion of water supply and/or wastewater treatment fees in some property taxes (Maffly 2022; Beecher and Kalmbach 2013; Rogers, da Silva, and Bhatia 2002). This lack of transparency in billing is a disincentive for conservation.

Though water prices often do not even recover the costs of supplying water, manufacturers generally think of water cost and water price as synonymous; they consider the amount paid to utilities for its use—similar to obtaining or using any other product/resource. However, the cost and price depend on whether the manufacturing facility purchases or self-supplies its water, leading to different costs and prices for each. Manufacturing facilities that purchase water from utilities are charged a certain price, typically based on the quantity of water purchased. These facilities tend to directly equate this price with the cost of water at their facility. In contrast, in most cases, self-supplied industrial facilities need not pay anything for their raw water input (Dachraoui and Harchaoui 2004). If any costs exist, their effective price could be the sum of the miscellaneous costs involved, such as abstraction licenses, infrastructure, and technology costs (UNEP 2014). In either case, manufacturers incur additional direct costs to use the water. Direct costs cover expenditures directly associated with establishing and maintaining the manufacturing facility's water supply infrastructure (e.g., circulating pumps and chemicals for treatment). In simple terms, they relate to costs associated with capital investment and O&M, including energy costs or even investing in water-conserving technologies.

As illustrated in Figure 3.1, the price of water use is a fundamental type of cost involved in industrial water use, but it is a small portion of the overall value of water. Price does not capture all the cost elements involved in industrial water use. Hence, the second innermost concentric circle in Figure 3.1 introduces the concept of true cost. In addition to the price, true cost includes ancillary costs at the facility, like those related to energy, chemicals, and permits. True cost is significantly higher than the conventional direct cost/utility price. However, it excludes both the costs associated with managing disruptions and the social costs related to scarcity and environmental externalities, known as indirect or opportunity costs. Other costs include those incurred by ensuring an adequate water supply meets production demands, such as securing an alternate supply of water or re-tooling equipment to use water of different quality. Indirect/opportunity costs represent the loss of potential benefits due to misallocation of a resource. Externalities are the economic or environmental costs imposed on third parties due to an activity over which these parties do not exert any control, and which are not reflected in the cost of the goods or services involved. For example, water pollution due to an industrial establishment could result in an increased cost of wastewater treatment for downstream users (economic externalities) or negative impacts to the ecosystem (environmental externalities) (CMAP, IISG, and University of Illinois Extension 2012). Social costs for industrial water use may be due to re-settlements resulting from water infrastructure expansion and scarcity of water or social conflicts like loss of income or employment opportunities from a lack of water resources.

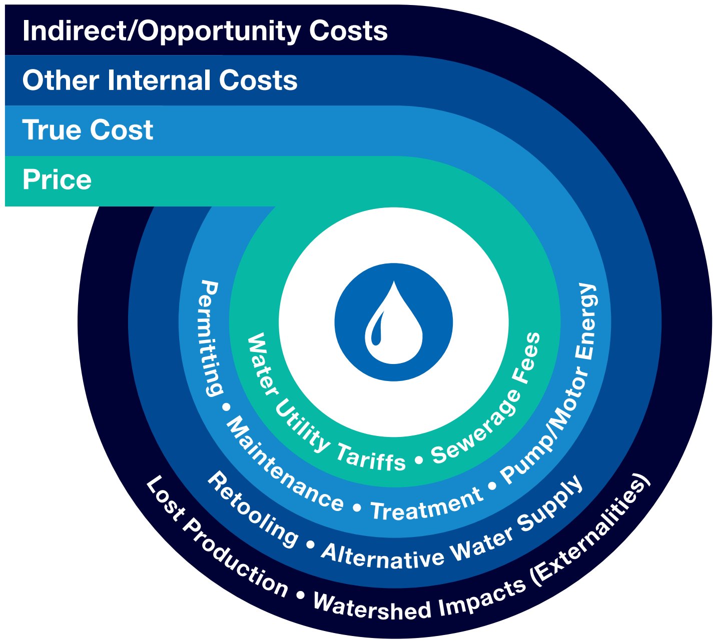

Figure 3.1 The value of water for manufacturers encompasses price paid to utilities or municipalities, true cost, other internal costs, and indirect/opportunity costs

Currently, in the manufacturing as well as other sectors, the full value of the services water provides remains externalized and thus unaccounted for. However, Figure 3.1shows a framework in which the full value of manufacturing water includes all costs depicted, as expressed in Equation 4, where true cost includes the price.

$$full\ value\ of\ water = true\ cost + other\ internal\ costs + indirect/opportunity\ costs$$

Equation 4

Figure 3.1 draws from the work done by Rogers, da Silva, and Bhatia (2002), in which the *full supply cost* contains O&M cost and capital charges, the *full economic cost* includes the full supply cost in addition to opportunity cost and economic externalities, and the *full cost* encompasses the full economic cost in addition to environmental externalities. Ideally, the full cost, as defined by Rogers, da Silva, and Bhatia, should be equal to the value, which includes the value to water users, net benefits from return flow, net benefits from indirect uses, adjustment for societal objectives, and the intrinsic value of water. The appropriate valuation of resources is essential for accurately evaluating various tradeoffs that arise when working to achieve sustainable resource use (Frame and O'Connor 2010).

3.2.1 Monetizing Water Beyond "True Cost"

The concept of the true cost of water is beginning to appear in corporate financial frameworks (ORNL 2019). However, the Other Internal Costs and Indirect/Opportunity Costs shown in Figure 3.1 are not often incorporated. Various types of risks caused by shocks, perturbations, and cross-sector competition to the industrial water supply can impact manufacturing operations. Even in the case of self-supply water withdrawals, water availability could be impacted, and the indirect/opportunity costs will go up. With drastic changes in climatic conditions on a global scale, adverse events could negatively affect manufacturing water supplies. These include acute events (short term events, such as droughts and floods) and chronic events (those that unfold slowly, like changes in agricultural growing seasons and large shifts in populations needing access to clean water). The acute events could create shocks and perturbations throughout the year, leading to periods of water unavailability, and the chronic events could exacerbate cross-sector competition for water supplies. Climate change highlights the urgency for industries to better monetize the potential impacts of future water risks on their manufacturing capabilities—and thereby the value of water beyond cost/price considered today and more aligned with the framing in Figure 3.1.

Water-associated risks that lead to economic impacts for manufacturers can be broadly classified into three types—physical, regulatory, and reputational (Morrison, Schulte, and Schenck 2010; Morrison et al. 2009). *Physical risks* arise from restricted access to adequate and reliable water supply, impacting its price irrespective of any uncertainties due to future water supply impacts. Causes of restricted water supply include

- Droughts or floods that damage the water supply infrastructure.
- Reduced water system capacity due to aging infrastructure and deferred maintenance.
- Changes in water availability (e.g., changes in snowmelt and timing of runoff).
- The cross-sector competition as mentioned above.

Regulatory risks refer to sudden changes in laws or regulations that alter a facility's access to water supplies/services and discharges. This risk type may affect the water cost associated with the discharge. *Reputational risks* arise from harmful production activities perceived to have negative water-related impacts, and these may subsequently cause damage to the ecosystem and decrease brand value or consumer loyalty. The value of water to the ecosystem is primarily characterized by these risk types—and industry today generally does not consider them. The type and nature of these risks depend on several factors, such as geographic location or even water use patterns, that are unique to each industrial sector. Section 3.3 reviews the variety of metrics used to both qualitatively and quantitatively analyze these risks.

3.3 Review of Water Valuation Methods and Metrics

Researchers have made limited attempts to quantify the value of manufacturing water use. Given studies' anticipated growth in the manufacturing sector, the localized effects of manufacturing water use will likely increase. The localization and agglomeration of facilities in specific regions could aggravate regional water scarcity. Within the manufacturing sector, using indicators in conjunction with water price can help to identify blind spots in achieving water use sustainability. In turn, this can help identify water uses that significantly affect production. If a facility finds a particular water use has a significant impact on production, it could act to improve the reliability of the water supply for that use. In particular, metrics are needed to measure the value of water and quantify trends/shifts. Such a class of metrics—herein referred to as water valuation metrics—can help identify where technologies are needed and evaluate their impacts.

3.3.1 Methodology

To accomplish the objectives of this study, it was essential first to establish the type of metrics that would most appropriately capture the valuation of water use in the manufacturing sector. An initial online search (through Google Scholar and Scopus) conducted in 2019 revealed a limited number of studies available on a global scale that attempted to quantify water use in the manufacturing sector. The authors excluded studies focusing on the cost and price of water use. Instead they prioritized studies focused on the valuation of water use in the manufacturing sector.

The authors formulated a search strategy to systematically target books and journal articles that discuss water use valuation based on the type of metrics identified in Section 3.3.2 (e.g., willingness-to-pay, value of marginal product, and elasticity). The search delivered limited studies on the manufacturing sector, primarily in the economics literature, and typically focused on developing countries in Africa and East Asia, where water scarcity has been a significant economic issue for decades. The search and subsequent filtering process produced 20 relevant technical literary sources. The primary criteria for selecting these studies were discussions of single or multiple water valuation metrics and their applications within specific industrial manufacturing subsectors (such as food, paper, plastics and rubber products, leather, steel, metal, etc.). The authors organized available metrics of water valuation estimates by metrics type, manufacturing sector, and countries/regions, including aggregate estimates. This approach facilitated understanding the application of these valuation metrics and their variation across different countries on both regional and global scales. Section 3.3.2 summarizes these water valuation metrics, examining willingness-to-pay, value of marginal product, and elasticity.

3.3.2 Summary of Valuation Metrics

With climate change increasing the risk of water scarcity, industries must assess their willingness to pay (WTP) beyond the cost/price paid today for their water needs. The *WTP metric* considers water risk types in terms of the maximum price at or below which a customer will definitely buy one product unit. Water WTP valuation techniques fall into two major categories, inductive and deductive, depending on the type and data level used for industrial value estimation (Young 2005b). The *inductive technique* applies primarily to a specific facility/industry and is based on real-world data to establish general relationships using a range of methodologies such as econometric, contingent valuation, and damage cost. On the other hand, *deductive techniques* such as value-added, computable general equilibrium (CGE), and alternative cost models are less data-intensive but more logical and analytically applicable for macro-level regional or country-wide estimation (Young 2005b).

Some other commonly used metrics to quantify the value of water are the *value of the marginal product (VMP)*, also known as the *marginal value of water*, average water productivity, shadow price, and elasticity coefficients. *VMP* represents the increase in output value per unit increase in water intake, while *average water productivity* is the total output divided by water input. Both are expressed in terms of $/m^3. The *shadow price of water* represents the intangible social opportunity cost of water (e.g., the value of a good that can be produced by the marginal unit of water used, given the quantity of the other inputs, e.g., labor and raw materials), also expressed in terms of $/m^3.

Elasticity is another frequently used water valuation metric employed to understand the degree of responsiveness of industrial water demand and output to variation in parameters. Accordingly, studies have analyzed two types of water demand elasticity metrics: (1) *price elasticity of water demand*, which depicts the change in demand for water with respect to a change in price (or cost) of water, and (2) *water elasticity of output*, which depicts the change in output per unit change in water input.

Subsequent sections discuss studies that apply these techniques and metrics to analyze and quantify the value of water through cross-industrial sector analysis, including a few on a regional scale.

3.3.3 Facility/Industry Water Valuation Methods and Metrics

Many industrial water valuation estimates rely upon econometric methods. These methods use an industry representation as a production process where the manufacturing output is a function of capital, labor, energy, materials, and water. Studies applying econometric methods to manufacturing subsectors represent them using NAICS codes. A production function approach is generally used to estimate the VMP of water, water average productivity, and the price and output elasticity of water demand. Examples of commonly used production functions include the Cobb-Douglas function and the translog function model. Regression techniques are then used to determine the coefficients associated with each independent variable. Researchers validate the model by applying standard statistical validations (e.g., R^2 value and f-statistics).

Figure 3.2 presents published water-value estimates for several countries at the 3-digit NAICS subsector level. The VMP is the most commonly used metric: the total number of published value estimates for the VMP is higher than the other two commonly used metrics— water average productivity and the shadow price of water. Ku and Yoo (2012) use two sets of value estimates based on two types of production functions (i.e., Cobb-Douglas and translog functions). Köseoğlu (2018) averages estimates from eight primary published studies. The estimates in Figure 3.2 were initially converted to U.S. dollars for the same year using the currency exchange rate (OECD 2019) and finally to the present value of 2021 U.S. dollars using the appropriate country GDP deflator (World Bank n.d.). Note that given U.S.-specific economic, legal, and regulatory frameworks, international estimates of water valuation may not apply to the U.S. context.

The leading industrial subsectors represented in Figure 3.2 and identified by NAICS codes are food manufacturing [311], petroleum and coal products manufacturing [324], chemical manufacturing [325], paper manufacturing [322], electrical equipment, appliance, and component manufacturing [335], textile mills [313, 314], and transportation equipment manufacturing [336]. The authors identified geographical location as a key factor for the variation in these estimates across different studies (e.g., Köseoğlu 2018; Fujii, Managi, and Kaneko 2012; Wang and Lall 1999). For example, the marginal values in water-scarce northern China are about twice the values in southern China based on the 1996–2006 period analyzed by Fujii, Managi, and Kaneko (2012). Industrial water-use efficiency improved during this period, as provinces in the northern region more efficiently reduced freshwater use. For similar reasons of high water scarcity and risk, Nahman and De Lange (2012) estimate the VMP of water in South Africa to be several orders of magnitude higher than other developed countries. All published estimates are for non-U.S. countries, but the two estimates for developed Western countries (i.e., Canada and the U.K.) may provide insight into U.S. water valuation.

Value metric		Value of water (2021$/m³)									
		VMP (marginal value of water)					Water average productivity		Shadow price of water		
NAICS code	Manufacturing sector/subsector	Köseoğlu (2018)	Ku & Yoo (2012)		Nahman & De Lange (2012)	Wang & Lall (1999)	Vásquez-Lavín et al. (2020)	Rojas (2005)	Fujii, Managi, & Kaneko (2012)	Kumar (2006)	Dachraoui & Harchaoui (2004)
		U.K. [Scotland]	Korea: Cobb-Douglas	Korea: translog	South Africa	China	Chile	Mexico	China	India	Canada
31-33	Overall manufacturing	6.35	2.17	1.55	59.43	0.74	9.44	166.54	0.3	7.7	1.3
311	Food	1.38	1.32	0.57	-18.63	0.77	29.94	518.6	0.2	-	0.27
312	Beverage & tobacco product	1.38	1.32	0.57	1009.67	0.77	-	269.04	0.27	-	1.3
313	Textile mills	7.94	0.74	0.91	93.86	3.44	9.66	445.56	-	9.82	-0.61
314	Textile product mills	7.94	0.74	0.91	93.86	-	-	445.56	-	-	0.07
315	Apparel	7.94	-	-	-	-	9.34	-	-	-	-0.37
316	Leather & allied product	-	-	-	-	5.23	2.62	-	0.05	-	1.64
321	Wood product	-	2.48	1.65	25.36	-	20.92	-	-	-	-0.03
322	Paper	2.93	2.48	1.65	25.36	0.25	5.93	77.91	1.24	2.22	0.88
323	Printing & related support activities	-	2.48	1.65	-	-	-	-	-	-	0.57
324	Petroleum & coal products	20.71	2.02	0.81	1237.58	1.81	-	-	0.06	12.36	2.48
325	Chemical	5.18	-	-	5115.76	0.3	10.12	159.48	0.12	7.36	0.55
326	Plastics & rubber products	-	-	-	-	-	8.5	-	-	-	3.5
327	Nonmetallic mineral product	-	3.86	4.49	-	-	8.18	-	-	-	-0.39
331	Primary metal	-	-	-	153.78	0.27	-	126.61	-	6.92	0.7
332	Fabricated metal product	-	-	-	-	-	-	-	-	-	-0.07
333	Machinery	-	4.19	1.73	0	2.66	5.07	-	-	-	-0.58
334	Computer & electronic product	-	1.6	1.67	1320.91	7.31	-	-	-	-	-
335	Electrical equip., appliance & component	7.07	5.21	2.63	1320.91	-	10.53	-	-	-	-
336	Transportation equipment	-	14.98	13.77	23.77	8.04	15.6	-	-	-	1.4
337	Furniture & related product	-	6.82	4.85	-	-	10.76	-	-	-	0.67

Figure 3.2 Marginal water value estimates for three metrics across country-wide manufacturing subsectors

Color distinguishes between metrics and darkest values highlight extremes.

Aside from marginal or average water valuation metrics, many included studies analyze elasticity. As with water value estimates, researchers generally derive industrial water demand elasticity from a production function. Most studies summarized in Figure 3.2 also estimate price elasticity or the output elasticity of water demand at the industry level as presented in Figure 3.3 and Table 3.1, respectively.

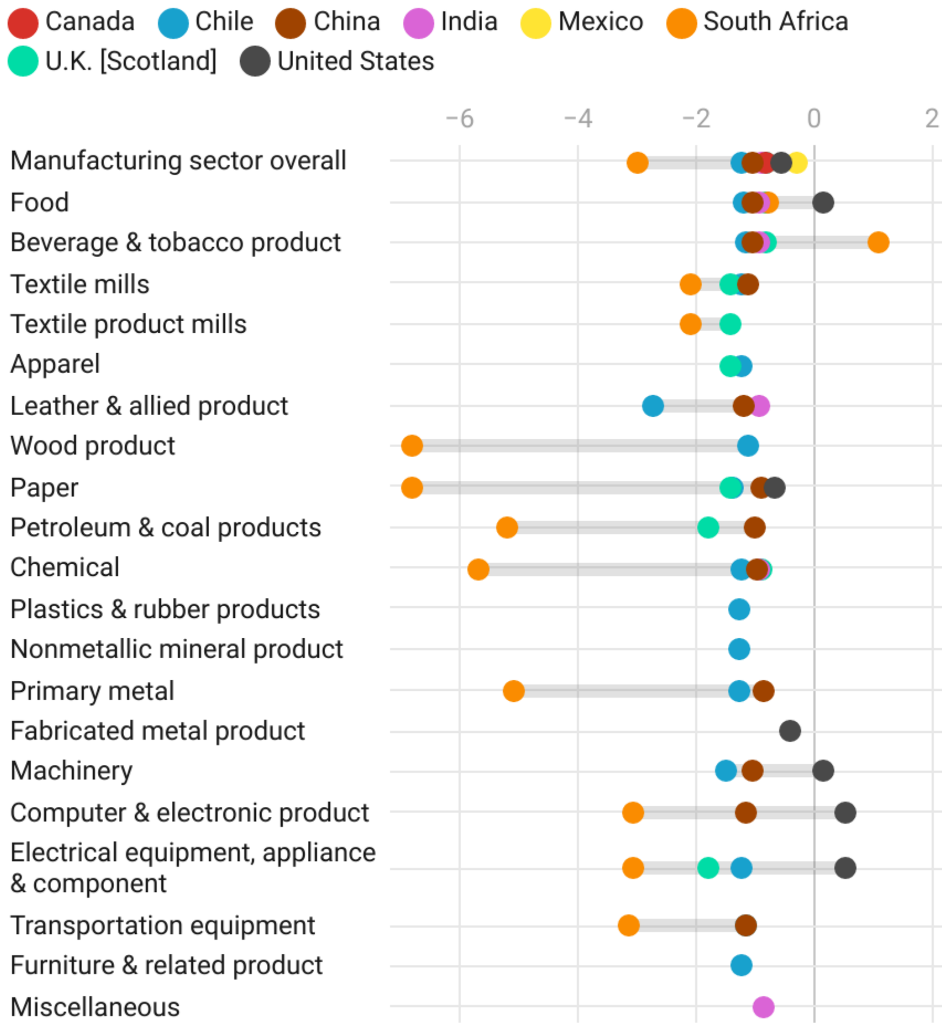

Figure 3.3 Estimated price elasticity of water demand across countries and manufacturing subsectors

References for each country follow the same order as the legend: Dupont & Renzetti (2001), Vásquez-Lavín et al. (2020), Wang & Lall (1999), Kumar (2006), Rojas (2005), Nahman & De Lange (2012), Köseoğlu (2018), Babin, Willis & Allen (1982). See Appendix B for full data table.

Estimates of industrial water demand price elasticity for the overall manufacturing sector (as shown in Figure 3.3)[25] were primarily negative, between 0 and -1, in the U.S., Canada, Mexico, the U.K., and India. This finding indicates that the water demand is relatively inelastic and signals that price increases would not necessarily be mitigated by, or cause a reduction in, water demand. Nahman and De Lange (2012) found the manufacturing water demand in water-scarce South Africa to be the most sensitive to prices (or cost), with price elasticities significantly greater than -1. A review of price elasticity estimates across 26 studies by Köseoğlu (2018) shows a pattern in elasticity based on industry type. Industries using water as a raw material, such as food and beverage manufacturing and chemical manufacturing, show

[25] Printing and related support activities subsector is not displayed in **Error! Reference source not found.** due to the lack of data

relatively inelastic demand compared with relatively elastic demand for industries using water as a process input, like textiles and apparel, paper, petroleum, and electrical equipment. For a few regional U.S. industrial subsectors, elasticities are estimated to be positive, although Babin, Willis, and Allen (1982) state that standard errors in the cases of machinery manufacturing, computer and electronic product manufacturing, and electrical equipment, appliance, and component manufacturing were large enough that these elasticities may not significantly differ from zero.

Some studies also estimate the cross-price elasticity of demand between water and other production inputs. The cross-price elasticity of water reveals its relationship to other production inputs. Cross-price elasticity of demand, $\in_{ij}$, is the percentage change in quantity of i^{th} input resulting from unit percent change in price of j^{th} input. The value of cross-price elasticity helps determine whether the inputs are substitutes (i.e., a unit increase in the price of one input leads to an increase in demand for the other inputs) or complements (i.e., a unit increase in the price of one input leads to a decrease in demand for the other inputs) in the production process. Positive cross-price elasticity means the inputs are substitutes, while negative cross-price elasticity means the inputs are complements. Cross-price elasticity of demand is zero if two inputs are not related. Estimates for the aggregate Mexican manufacturing and mining sector from Rojas (2005) for cross-price elasticity of water with other inputs show that water is a substitute for both labor and material. Kumar (2006) found water to be a substitute for capital but a complement to materials and labor for all industries, while Vásquez-Lavín et al. (2020) found water to be a substitute for capital, labor, and material but a complement to energy. In their study on water use for Canadian industries, Dupont and Renzetti (2001) included two variables in the production function for water use: water intake and water recirculation. As expected, water intake and recirculation are substitutes, and the former parameter is a substitute for capital, labor, and energy.

Output elasticity of water demand is an alternative elasticity metric. It is denoted as positive values to estimate the output impacts of returns to scale[26] from changing the water intake. An output elasticity of water demand of 0.5 would mean that a 1% increase in manufacturing output is associated with a measured water demand increase of 0.5% (Gardiner and Herrington 1986). Table 3.1 shows limited estimates of various industrial subsectors from two studies (Ku and Yoo 2012; Wang and Lall 1999). A range of estimates from Ku and Yoo (2012) corresponds to the two types of production functions used (Cobb Douglas and trans-log). Output elasticity of water is significantly small, less than 1, implying an increase in water use does not lead to an increase in final product output (quantity). The studies do not find that water availability is a major factor of the final manufacturing output for these two countries.

[26] The economic concept of *returns to scale* explains how increases in production (or output) are linked in the long run to associated increases in the inputs. Returns to scale can be constant (e.g., when inputs increase by 50%, output increases by 50%), increasing (e.g., when inputs increase by 50%, output increases by more than 50%), and decreasing (e.g., when inputs increase by 50%, output increases by less than 50%). Increasing returns to scale are typically driven by companies using more sophisticated technologies to streamline and specialize production; decreasing returns to scale can occur via difficulties managing increased production and/or a lack of coordinating production stages.

Table 3.1 Output Elasticity of Water Demand Comparison of Manufacturing Subsectors in Two Countries

NAICS code	Subsector	Output elasticity of water demand Ku and Yoo (2012) Korea	 Wang and Lall (1999) China
31-33	Manufacturing sector	0.02; 0.01	0.17
311	Food manufacturing	0.018; 0.008	0.17
312	Beverage & tobacco product manufacturing	0.018; 0.008	0.17
313	Textile mills	0.016; 0.017	0.21
314	Textile product mills	0.016; 0.017	-
315	Apparel manufacturing	-	-
316	Leather & allied product manufacturing	-	0.26
321	Wood product manufacturing	0.022; 0.014	-
322	Paper manufacturing	0.022; 0.014	0.1
323	Printing & related support activities	0.022; 0.014	-
324	Petroleum & coal products manufacturing	0.028; 0.012	0.15
325	Chemical manufacturing	-	0.13
326	Plastics & rubber products manufacturing	-	-
327	Nonmetallic mineral product manufacturing	0.042; 0.048	-
331	Primary metals manufacturing	-	0.09
332	Fabricated metal products manufacturing	-	-
333	Machinery manufacturing	0.016; 0.0067	0.17
334	Computer & electronic product manufacturing	0.01; 0.011	0.23
335	Electrical equipment, appliance, & component manufacturing	0.024; 0.012	-
336	Transportation equipment manufacturing	0.04; 0.036	0.24
337	Furniture & related product manufacturing	0.035; 0.025	-
339	Miscellaneous manufacturing	-	-

3.3.4 Regional/Economy-wide Water Valuation Methods and Metrics

Shifting the focus from facility-level valuations to regional valuations enables policy on industrial water use to advance technology uptake. Water valuation metrics used at the regional- or economy-wide level are based on the analysis of macro-level regional data used to estimate regional-scale water-related economic impacts. A comparatively limited number of studies use metrics in this area. Table 3.2 shows estimates from such studies. Average and median water value estimates from Frederick, Vanderberg, and Hanson (1996) were based on multiple methods, such as average and marginal metrics, using the production function approach, and contingent valuation techniques for nonmarketed services from 41 different studies.

Most of the studies in Table 3.2 aimed to evaluate existing water usage policies within a given geographical region to understand the obstacles hindering sustainable water supply/use and resultant economic growth. Some studies employed quantitative analyses to estimate the intangible avoided cost not considered by conventional metrics, such as shadow price ($\$/m^3$) or other economic parameters, like the potential loss of jobs or economic output. Table 3.2 also includes studies that conducted qualitative analysis to identify the potential risks associated with these obstacles and the resultant economic impacts (Cobti, Kotsantonis, and Williams 2017; Mueller et al. 2015). These studies quantify obstacles via scores ranging from 0 to 5 to convey the degree of risk associated with water scarcity.

Researchers estimated these metrics using deductive techniques, for example, CGE models or input-output model techniques. CGE models use actual economic data to estimate how an economy might respond when stimulated by changes in policy or other external factors. Feng et al. (2007), a classic example of such a study, use the CGE model to determine if additional water supply from a large-scale water transfer project would help overcome potential obstacles due to regional water resource vulnerability. Another unique modeling approach observed was the meta-frontier model analysis technique adopted by Li and Ma (2014), which attempted to identify the policy changes needed to address low industrial water use efficiencies in industrial firms across 30 different Chinese provinces. The analysis also quantitatively established that the estimated average shadow price was 12 times higher than the actual average price of industrial water across mainland China's eastern, central, and western regions (Li and Ma 2014).

Table 3.2. Reviewed Studies on Regional/Economy-wide Manufacturing Water Valuation

Study	Country	Estimation metric for industrial sector	Method	Data sources	Estimated value
Hall (2019)	Athens-Clarke County (U.S.A)	• Jobs lost • Reduction in Gross Regional Product (GRP)	IMPLAN, a risk-based industry standard input/output economic model: used to understand sensitivity to 15–20% reduction in water use	2014 county data for 536 economic sectors	Reduction in the GRP of $244M and 4,171 jobs lost
Cobti, Kotsantonis, and Williams (2017)	Global scale	Quantitative scores for vulnerability and resilience between 1 (low risk) to 5 (high risk)	Water risk exposure estimated on regional scale and industrial scale	Data from 50 publicly listed global companies through: • WWF / DEG water filter tool • SASB materiality map • WRI Aqueduct tool • Ceres Aqua Gauge tool • CDP water survey	-
Mueller et al. (2015)	India, USA, Mexico, China, Brazil, Spain	Quantitative risk indicator scores (between 0 to 5)	Evaluation of 4 open-source water risk assessment tools	GPS coordinates and water use data for each location, for each industrial sector	-
Li and Ma (2014)	China (30 provinces in mainland China)	Shadow price	Meta-frontier model analysis	China environment Statistical Yearbook (2000–2014), focused on data from 30 provinces	6.3 (2021 $/m^3)
Feng et al. (2007)	China (based on South to North Water Transfer Project)	Shadow price	Computable General Equilibrium model (CGE)	Water resource fee data from Water Social Accounting Matrix database	6.62 (2021 $/m^3)
Frederick, Vanderberg and Hanson (1996)	United States	Average and median water value (overall)	Review of water value estimates from multiple studies	7 estimates of water value for industrial processing	0.38 (2021 $/m^3)

Input–output models have also been applied to quantitatively analyze regional-level data to understand any change in production output due to a change in industrial water supply. A study conducted in Athens-Clarke County (GA, USA) used this approach to quantify the risk of drought occurrence to potential industrial jobs lost and loss of economic output in the absence of any water conservation measures (Hall 2019). Using the county-level data for 536 economic sectors, Hall (2019) estimated adverse economic impacts, including a gross regional product (GRP) reduction of $244M and the loss of 4,171 jobs, even at a 5% risk of drought occurrence. Most of these studies focus on valuation efforts for specific geographic locations within a country. A complete country-level analysis is inappropriate due to a wide variation in both spatial and temporal water use, requiring a vast range of data and parameters for complete analysis.

3.4 Case Studies of Water Valuation by Manufacturers

The Millennium Ecosystem Assessment[27] estimates that in the last half of the twentieth century, urbanization, industries, agriculture, forestry, and fisheries have driven the decline of 60% of all ecosystem services (e.g., carbon sequestration, freshwater provision, air and water quality regulation, storm protection, disease control, and habitat provision), in large part because the benefits of these public goods are generally not priced, so markets rarely mirror the full social and environmental cost of production (Kinzig et al. 2011). Another estimate signifying considerable pressures on the ecosystems on which economies rely is that global production systems externalize $4.7T annually in environmental costs (O'Rourke 2014). The effective development of payment for ecosystem services (PES) mechanisms and physical indicators of ecosystem health are examples of the types of better incentives, data, and decision-support tools that will be critical for companies to quantify and manage environmental impacts and business disruption risks across the production life cycle (Kinzig et al. 2011; O'Rourke 2014). Further, incorporating PES into internal corporate water management practices can lead to wider adoption of water-saving technologies.

While the appropriate valuation of water in the manufacturing sector is nascent, several multinational corporations have made strides in the last decade. For example, within the apparel industry, supply chain sustainability initiatives concerning the water use of production include the Better Cotton Initiative, the Sustainable Apparel Coalition Higg Index, PUMA Environmental Profit & Loss, Levi's E-valuate and Water<Less, Nike ColorDry and FlyKnit, Zero Discharge of Hazardous Chemicals, and Levi's Wellthread (O'Rourke 2014). In 2011, the footwear and apparel company PUMA published an Environmental Profit and Loss (EP&L) Account encompassing the cradle-to-gate impact of its products on ecosystems, appraising the cost to society of the water used in PUMA's supply chain as €47M per year—on par with greenhouse gas emission costs (PUMA 2011). PWC and TruCost modeled this estimate using a relationship between water scarcity and value derived from a comprehensive literature search in order to evaluate in economic terms the drop in the direct use value of water to third parties as a consequence of PUMA's water consumption. As a result of the EP&L accounting, PUMA is

[27] The Millennium Ecosystem Assessment synthesized the work of more than 1,360 experts globally to evaluate the impacts of ecosystem change on human well-being. https://www.millenniumassessment.org/en/index.html

now focusing on its supply chain (specifically, water to grow cotton and make leather) rather than on its own operations to reduce its water impacts.

Another large multinational investigating water valuation is Unilever, a consumer goods company with more than 250 manufacturing sites worldwide. The Unilever Sustainable Living Plan has identified water shortages and poor water quality as risks to continuous business operations, with recent droughts in Taiwan, Brazil, and Poland potentially threatening to disrupt production (Gohil and Méndez Vives 2016). Working with Unilever, MIT researchers used the WRI Aqueduct tool to identify numerous business disruption scenarios related to water, estimated their likelihood and consequences, and determined available mitigation options to create a risk-adjusted value of water aggregated across all event scenarios. Table 3.3 demonstrates the substantial differences between the true value and the purchase price of water for four modeled Unilever plants.

Table 3.3 True (Risk-Adjusted) Value of Water Estimates in Four Cases of Unilever Plants

	Case 1	Case 2	Case 3	Case 4
Product category	Laundry products	Laundry products	Beverages	Hair products
Baseline water stress	3.61	5	0	0
Days of inventory	7	0	2	1
Purchase price of water (2016$/m^3)	2.36	0	0.14	0.62
Process & handling cost (2016$/m^3)	0.62	0.62	0.62	0.62
Business disruption cost (2016$/m^3)	0.77	8.94	2.09	1.63
True value of water (2016$/m^3)	3.75	9.56	2.85	2.87
% increase from purchase price to true value of water	**59%**	**N/A***	**1936%**	**363%**

*Cannot divide by zero. Source: Adapted from Gohil and Méndez Vives (2016)

The variation in each site’s value-at-risk, or business disruption cost, could help Unilever incentivize water efficiency and basin-based stewardship initiatives where and when most crucial, improving the resilience of its manufacturing operations via more optimal water use.

In Texas, the Dow Chemical Company partnered with The Nature Conservancy to better understand water risks for its Freeport Facility on the Brazos River. One effort involved hydro-economic modeling to characterize future water availability in the Brazos River basin and project the scale of economic losses from future water shortages (Reddy et al. 2015). A conservative approximation of loss due to water shortages affecting this single facility was $900M (30-year NPV). More broadly, this study underlines that the potential implications of cross-sector competition and the benefits of water markets, in which agricultural users sell their water to municipal and industrial users, are lessened in the context of industrialized or water-stressed river basins. It also presents a methodology for businesses to inform strategic planning processes via evaluating basin-scale water risks. As a result, the facility tracked indicators of water supply shortages, conveyed risks associated with industrial and municipal-dominated basins, and explored options outside of water trading. The same researchers extended their analysis by using natural capital asset valuation to calculate the changing value of all industrial water rights in the Brazos River basin under varying water demand and climate change scenarios (Reddy et al. 2015). Employing multi-criteria analyses for water scarcity solutions using private, public, and biodiversity-related costs and benefits revealed that three scenarios are competitive on cost with the business-as-usual solution of increased reservoir storage. However, because these scenarios provide collective benefits to other water users and ecosystems in the basin while individual stakeholders bear the costs, more widespread payment for ecosystem services or water funds are necessary to correctly align incentives.

Finally, the apparel company Patagonia calls for the widespread adoption of value chain indices (VCI) to bring the previously externalized environmental and social costs of production inside and onto individual firms' balance sheets (Chouinard, Ellison, and Ridgeway 2011). A VCI quantifies ecosystem services (e.g., for water, land use, and carbon) in dollar terms on the basis of cradle-to-grave production impacts and should ideally be developed jointly by various competitors in a sector and draw on objective life cycle analysis databases. Achieving "true cost accounting" would enable manufacturers to find improvements throughout their value chains while "powerful market forces would be put in the service of sustainability's goals" (Chouinard, Ellison, and Ridgeway 2011).

3.5 Conclusions

Generally, to date, the manufacturing industry has not incorporated water scarcity when valuing water. In addition to the true cost, the value of water must include the indirect/social costs associated with industrial water use. A fuller monetization of water that incorporates the ecosystem impacts from its use and the costs associated with the realization of various water risks will create a more fertile environment for developing water-saving technologies and implementing conservation efforts. Until then, technology development and conservation efforts will be stymied by the common refrain that "water is too cheap".

This section reviews and summarizes the economic valuation literature to present general trends regarding the valuation of water use in manufacturing. It highlights the need to incorporate the true cost of water, indirect/opportunity costs, and other costs associated with the realization of water risks into the value of water. Indirect/opportunity costs include revenue loss from reduced production due to lost or curtailed water supplies, as well as environmental impacts associated with water use and wastewater disposal. Costs associated with water risk realization include the costs of finding and utilizing alternate water sources and retooling a plant for water substitutes. Three types of risks could trigger such costs: physical, regulatory, and reputational.

Most studies indicate that the marginal value of manufacturing water use is typically higher than the price (or cost) of water supply, indicating the need for manufacturers to use value estimates rather than cost estimates for water risk evaluation. Available water valuation estimates based on a range of different metrics, both at the industrial and regional scale in terms of a change in value per unit of water use, indicate wide variability not only across different manufacturing subsectors and locations within a study, but also across various studies for a manufacturing subsector.

Valuation metrics that consider a change in value with a change in the quantity of water used, such as VMP, shadow price, and elasticity, are appropriate for evaluating the economic competitiveness of water conservation technologies. Elasticity is one metric used to understand how water demand responds to price and process output. Subsectors using water as process inputs (like paper, textile, and electrical industries) have relatively elastic price demand compared to subsectors that use water as a direct input to production (like food and beverage industries, which would need to maintain a consistent water use rate to maintain constant production output). This implies that the effect of pricing on water conservation would be higher for the former subsectors. Alternative econometric valuation estimation methods used historically are data-intensive, and the limited availability of such manufacturing data makes their implementation difficult to accurately predict future valuation. The appropriate water valuation metric will be case-specific considering both regional and temporal risks. Industrial sectoral level valuation analysis is critical to the overall regional water valuation (using some of the macro evaluation techniques, e.g., computable general equilibrium modeling and input-output modeling) for the estimation of indirect local economic impacts from reductions in water availability for the manufacturing sector, such as job and GRP losses.

Finally, several recent case studies of manufacturers provide examples for others while illustrating both the promise and challenges of water valuation. While the environmental and social costs of manufacturing water use are still externalized, some large multinational corporations have moved toward assessing the value of water via supply chain sustainability initiatives, environmental profit and loss accounting, estimating risk-adjusted values of water, hydro-economic modeling, natural capital asset valuation, and developing value chain indices.

Future work in this area could involve employing the information summarized in this section to develop guidance or a specific methodology for the valuation of water for use in the manufacturing sector that encompasses the full extent of associated economic and environmental impacts. The emergent linkages between economic valuation and virtual water (or water footprint) (Horlemann and Neubert 2006; Lowe, Oglethorpe, and Choudhary 2018) could be examined in the manufacturing context to understand more about how valuation metrics of virtual water inputs (e.g., raw material inputs) would assist manufacturers in evaluating the reliability of their suppliers. In addition, researchers collaborating with industry to develop and disseminate case studies on the implementation of water valuation metrics may help make the case for more widespread adoption of such approaches. Manufacturers that integrate the full value of water into decision-making are better able to achieve sustainability goals by justifying expenditures on water conservation technologies, planning for water-related risks, incentivizing water efficiency and stewardship, enhancing their reputation among customers and shareholders, and improving the resilience of their operations.

4. Technologies and Engineering Supporting Resilience Strategies

4.1 Introduction

Section 1 of this report argues that myriad water-related risks and water resilience should motivate more efficient and sustainable water use in the manufacturing sector. However, resilience is difficult to quantify both in a physical and economic sense. Section 4 provides exemplars of the types of analyses that align with this framing of risk and resilience. The authors present these example strategies to encourage other researchers, industry leaders, and policymakers to generate more ideas and innovations in this space.

Industries that are some of the largest water users include food and beverage manufacturing, chemicals manufacturing, textile manufacturing, pulp and paper manufacturing, automobile manufacturing, and semiconductor manufacturing. Several manufacturing companies within these industries have incorporated water conservation and resilience initiatives into their sustainability programs (EPA 2012; Koel 2013; Manganello 2019). All these initiatives are primarily based on implementing water stewardship programs in partnership with local communities to reduce the manufacturing industry's dependency on water. As noted in their respective corporate social responsibility and environmental stewardship reports, water resilience approaches for these industries typically entail the following:

(1) reducing the water intensity per unit of product via increased water efficiency and water recycling/reuse,

(2) identifying alternative water sources,

(3) reducing water pollution by going beyond minimum standards of treatment and treating a broader range of pollutants, and

(4) working with local public works utilities and watershed management agencies.

This section dives more deeply into these four approaches.

First, this section summarizes specific measures that enhance water use resilience in manufacturing. It then presents a tool that assesses the true cost of water at manufacturing facilities by effectuating some of the concepts around water valuation presented in Section 3. The tool outputs underscore that measuring all the costs associated with water use enables identifying cost-intensive operations for which optimizing water use would result in significant financial benefits.

Next, the authors present several advanced strategies, both inside and outside the manufacturing fenceline. Inside the fenceline, Section 4.4.1.1 explores the potential of water use substitution/efficiency within the context of "dry factories," yielding important sustainable design considerations for assessing new technologies. In addition, Section 4.4.1.2 presents a framework that elucidates the tradeoff between on-site water reuse and its additional energy consumption to help identify beneficial reuse opportunities. Outside the fenceline, a case study in Louisiana (Section 4.4.2.1) demonstrates the application of a theoretical framework developed to optimize the embedded energy, greenhouse gas emissions, and resilience of manufacturing water supply portfolios.

Finally, the section closes with Section 4.4.2.2, an analysis of the opportunity space for increasing the coordination between water and electricity systems such that flexible industrial water treatment could provide additional revenue for manufacturers, reduce electricity prices, and contribute to grid stability.

4.2 Water Use Resilience Enhancement Strategies in Manufacturing

Section 4.2 Summary

- Water resilience enhancement strategies aim to minimize the negative effects of water-related outages on the volume, pressure, quality, or other essential aspects of water. These strategies are designed to reduce both the exposure to such outages and the time required for recovery. Implementing these measures can safeguard manufacturing operations and the watershed's overall health against adverse consequences.
- To reduce water usage and increase efficiency in manufacturing operations, various measures can be adopted, including conserving water through heat exchanger networks to reduce boiler feedwater demand, servicing and retrofitting cooling systems, and exploring alternative water sources like gray water.
- Manufacturing unit processes can be modified to consume less or no water, for example, by using gas-based technologies (e.g., carbon dioxide-based coolants and cleaning solutions, laser ablation, etc.) to provide heat and mass transfer, dissolution, or other functions typically served by water.
- Water reuse can be incentivized by treating and utilizing gray water for non-production purposes, either through separate water systems or a combination of potable and recycled water sources.
- Enhancing the robustness of the water supply involves diversifying water sources, implementing multiple inlet pipes, and maintaining water storage and distribution infrastructure. Companies should conduct life cycle assessments to reduce the water footprint of manufacturing and mitigate water-related risks in supply chains.
- Elements of Section **Error! Reference source not found.** draw from the following work published by report authors: Supekar et al. (2020).

Resilience enhancement options seek to maintain reliable, sustainable, and affordable sources of water supply to decrease potential negative consequences on manufacturing operations. The objective typically is to minimize the occurrence of outages leading to a degradation of water characteristics (i.e., volume/availability, pressure, and quality), although it may also, in some cases, factor in the effects on local watersheds. Several options may be considered to change water requirements, reduce water usage, and increase the efficiency of manufacturing operations. They are discussed here in the context of measures and strategies that industries and policymakers can strive to adopt and incentivize.

Freshwater use—and, by extension, wastewater production—should be minimized by conserving water. One promising approach to reducing water use at manufacturing facilities is adding heat exchanger networks to industrial boilers to collect and return condensate to the boilers, thereby reducing feed water demand. However, boilers cannot perpetually operate in a closed loop. Water from the boiler loop should be removed and replaced periodically to avoid accumulating minerals in boilers and pipes. In addition, facilities should regularly service or retrofit cooling systems to reduce potable water use and consider using grey water from other manufacturing processes in cooling systems. Switching from water-based cooling to air-cooled systems presents a greater opportunity for water conservation at the expense of increased energy consumption and a larger physical footprint. See Karki and Rao (2023) for a detailed techno-economic analysis of water efficiency measures in the manufacturing sector, which could reduce U.S. manufacturing water use by 60%.

Another approach to water conservation would modify manufacturing unit processes to varying degrees. Relatively minor changes such as using intermittent-flow instead of continuous-flow systems for rinsing procedures and reducing washing frequency for equipment could significantly help water conservation. A more transformative approach is to fundamentally modify manufacturing unit processes so that they consume substantially less or no water at all. Research, development, demonstration, and deployment activities have yielded a new generation of equipment and environmentally friendly technologies that promote alternatives to water. These alternatives include using enzyme products, cryogenics, dry saturated steam, ultrasounds, ozone, pulsed lights, and chemical-lean processes (Agromedia 2015). As one example, metalworking operations in which oil-water emulsions are used as coolants and lubricants could use gas-based technologies instead. Such gas-based systems, in which the delivery medium for the lubricant is an industrial gas such as compressed air, carbon dioxide, or nitrogen instead of water, can provide comparable or better cooling and lubrication performance (Supekar et al. 2020). For more on these systems, refer to Section 4.4.1.1. Thermodynamic cycles that use carbon dioxide as a working fluid instead of water present another waterless technology opportunity when deployed in combined heat and power plants in manufacturing facilities (Crespi et al. 2017).

In manufacturing processes where water is used as a solvent or cleaning agent, such as surface cleaning of manufactured parts (e.g., engine components, foods, semiconductor wafers), carbon dioxide-based cleaning technologies or laser ablation could again serve as water-less alternatives (Zhou et al. 2002; Beckman 2004; Aresta and Dibenedetto 2007; Bach, Cleve, and Schollmeyer 2010; Supekar and Skerlos 2014a). These alternatives remain very expensive, but they could become more competitive given water scarcity. It is important to note that industrial gases used in many such “water-less” technologies are quite energy-intensive to produce. Therefore, in addition to costs, it is critical to examine the life cycle water and energy use of such technologies to understand and mitigate any tradeoffs. Further, since the driver behind these alternative technologies is the need to improve the resilience of industry to supply disruptions (of water in this present discussion), it is imperative to examine the supply chains of alternative technologies to ensure that, for instance, the source of vulnerability is not shifted from water supply to industrial gas supply.

Turning from conservation to reuse, the incentive to reuse water seems directly related to the cost associated with accessing and treating raw water. Grey water from processes such as washing and rinsing is not considered safe for human consumption, but with minimal and appropriate treatment it could be used for processes that do not require high-quality water (e.g., some rinses, non-contact cooling, and landscape irrigation). Specifically, two main options exist for using recycled water in sprinkler systems, a non-production process application (Hickey 2008). In one option, a system combines both potable municipal water and recycled water sources to improve the water system's reliability. For instance, such a system could allow the use of recycled grey water in the event of disruption or contamination of the municipal water supply. This option requires control and back-flow monitoring to avoid cross-contamination of the potable water distribution system. The second option separates the potable and non-potable water systems, such that non-potable water is used in building fire suppression sprinklers or lawn sprinklers and the potable municipal water supply system is used for production processes with more stringent quality requirements.

Similarly, non-potable water sources such as effluent, wastewater, rainwater, brackish or mineralized water, seawater, and irrigation return flows must be evaluated where appropriate, for example, in fire suppression or in some production processes. Non-potable water could require specific treatments to remove any inorganic and organic components that could damage the pipes. Appropriately using recycled water and/or water from alternative non-potable sources would provide better flow rates and, thus, overall reliability of supply for both potable and non-potable water and could potentially reduce operating costs. In the case of potable water requirements, however, treatment can be expensive because backup treatment systems may not be fully equipped to handle requisite wastewater treatment steps.

At the same time, avoiding relying on a single water inlet or pipe connection into an industrial facility could make the water supply more robust. Multiple connections entering the facility at different locations would help eliminate or mitigate the impact caused by disruptions or breaks in any one connection. Another important measure to enhance the robustness of water supply is to use water towers and water tanks as buffers to balance supply and demand. Water stored in these buffers could be used in case of disruption of main supplies. However, adding water storage can be costly and/or infeasible for smaller industrial facilities. Even when feasible, adding water storage can support most facilities for only short periods. The best redundancy and robustness options remain diversifying water supplies by adding multiple inlet pipes to a facility, finding alternative water sources, and implementing adequate maintenance schedules for the water treatment and distribution infrastructure.

These strategies and actions are aided by a comprehensive and life cycle assessment of the use of water in order to reduce the manufacturing water footprint and the water embedded in manufactured products. Manufacturers should conduct life cycle assessments to better account for risks along their supply chains and reduce vulnerability to potential water scarcity. Examples of this approach are found in textile manufacturing at Levi Strauss & Co., with sustainability initiatives to reduce environmental impacts along the entire life cycle of denim apparel from cotton production to their disposal (Levi Strauss & Co. 2022), and in automobile manufacturing at the PSA Group, which favors a global approach throughout the product life cycle (PSA Group 2019). Although such water conservation measures often emanate from environmental sustainability considerations, they may often synergistically improve the water resilience of these industries (Marchese et al. 2018).

4.3 Measuring the True Cost of Water at Manufacturing Facilities

Section 4.3 Summary

- As Section 3 discusses, the value of water greatly exceeds the price of water, and several metrics have been developed to illustrate this, including the true cost of water.
- The true cost of water goes beyond the acquisition price and can include substantial costs for energy additions (pumping, heating) and quality improvements (treatment and disposal).
- Accounting for the true cost of water can help identify cost-intensive operations and make water efficiency measures more economically attractive; DOE's Plant Water Profiler tool can be helpful.
- Use of the Plant Water Profiler tool at three manufacturing facilities demonstrates the true cost of water can be 1.3–3.2 times the acquisition price.
- Accurate metering and submetering of water use, intakes, and discharge helps facilities understand their water use and better plan resource optimization efforts.
- Elements of this section draw from the following work published by report authors: Armstrong, Garcia, and Nimbalkar (2020).

As the uncertainty of sustained water supply (Borgomeo, Hall, and Guillod 2018; Orr, Cartwright, and Tickner 2009), regulatory constraints (Gouws et al*.* 2010), competition among end users (UN 2007), and public scrutiny (Morrison 2009) increases, a growing number of manufacturers are adapting to current and emerging water-related risks by optimizing productivity and reducing waste. To move toward increasing water use efficiency and making informed business decisions, corporations must try to understand and track their water demands, losses, and costs associated with each subsystem within their facilities. The work in this section draws from a national laboratory report by Malhotra et al*.* (2021).

Given the low price of water, manufacturers are often unaware of the "true cost of water," which reduces the visibility of the actual impact of water-saving measures. The true cost of water in a facility goes beyond the price paid for water acquisition (e.g., via municipal providers) and must be quantified in the context of the water-energy nexus (e.g., cost of energy for pumping and heating) and account for changes in water quality (e.g., cost of treatment and disposal). In addition to potential cost reductions and energy impacts, water-saving measures can benefit the surrounding environment (EPA 2011).

To help manufacturers account for water procurement and use in manufacturing operations, quantify the true cost of water, and identify potential areas for water and associated energy cost savings, an open access tool—Plant Water Profiler (PWP)—was developed. The tool is based on water mass balance analysis and has been adopted by the U.S. DOE Better Plants program as the core analysis tool for its plant water use assessments, Water Efficiency In-Plant Trainings (INPLTs). During three pilot INPLTs conducted in 2019 at three manufacturing facilities, the PWP tool allowed users to understand water flows within the facilities and provided additional capabilities to analyze their water use. The three case studies demonstrate opportunities to improve water efficiency and reduce associated costs.

Several tools have been developed in the past to manage water use (e.g., spreadsheets, audits, and scorecards [AWWA 2006; EDF-GEMI 2014; FEMP 2023]); assess facility water balance (e.g., GEMI's Collecting the Drops [GEMI 2002], Blue Plan-It [Carollo n.d.]); and determine the true cost of water (BIER 2018; Colgate-Palmolive 2015; Veolia 2013). Moreover, large water-intensive companies have also developed their own systems as part of their environmental stewardship programs [e.g., PepsiCo Resource Conservation (ReCon) (PepsiCo 2017), Nestle Environmental Management System (NEMS) (Nestlé 2013)]. Tracking water use with any tool is the first step toward identifying water-saving opportunities. The assessment of true cost can bring additional benefits by allowing facilities to compare water-saving opportunities based on water volume and monetary costs. This effort produces a clear vision of the resources needed to implement water-saving strategies (e.g., energy for pumping, chemicals for treatment, and associated costs) and may help operators demonstrate, in economic terms, the benefits of their strategies.

4.3.1 Plant Water Profiler Implementation

Through DOE's Industrial Efficiency and Decarbonization Office (IEDO; previously the Advanced Manufacturing Office (AMO)), ORNL offers support to Better Plants program participants through Water INPLT through multi-day workshops performed by industry-recognized experts. The Water INPLT program, based on the INPLT model by Alkadi et al. (2013), includes both classroom and field-based sessions and trains attendees to identify water-saving opportunities, estimate savings, and implement projects (Guo et al. 2019). For three pilot trainings conducted during the second half of 2019, attendees used the PWP tool as the core analysis tool for plant water use assessment and true cost calculation. The facilities benefiting from the INPLT were an iron and steel manufacturing plant, a fiberglass manufacturing plant, and a vinyl siding manufacturing plant. The training sessions included "treasure hunts," facility-wide assessments in which cross-functional teams of employees compete to identify operational and maintenance-related energy and water efficiency improvements.

Quantifying the true cost of water at a facility encourages the use of high-granularity data. However, it is well known that there are challenges in submetering water flows in the manufacturing sector. When data cannot be collected, analysts can apply indirect estimation methods of water use through parameters such as hours of operation or estimated evaporation rates. This approach has drawbacks and may not allow facilities to properly identify losses and opportunities. Only through continuous metering and submetering of water, by using appropriate tools to track water-use variability, and by assessing the water mass balance can facilities acknowledge opportunities for improvement in the identification of losses from water leaks, increased costs of wastewater treatment due to stormwater intrusion, as well as water recirculation opportunities. Proper submetering can also establish a baseline scenario to track-water saving strategies during subsequent years.

Implementing the PWP tool in the past has helped facilities identify components that contribute the most toward the facility's true cost of water and the most water-intensive subsystems. In one case, the PWP tool showed that maximizing recirculation water used in cooling towers could potentially save 40–70 gallons of water per 1000 sq ft production unit of polymer siding (Armstrong et al. 2019). This analysis was conducted for a facility that manufactures polymer siding made from polypropylene resin using an injection molding process. Within the facility, water cools operations such as injection molding machines, injection molds, and conveyor air handlers.

Water-using subsystems in industrial manufacturing plants may include processes, cooling and condensing subsystems for process, power generation, and air-conditioning; steam boilers for power generation; and ancillary services such as kitchen, restrooms, landscaping and irrigation, and fire sprinkler subsystems. Figure 4.1 shows the breakdown of source water intake and the true cost of water by subsystem and cost component for each of the three facilities evaluated (Malhotra et al. 2021). The water classified as process water tends to be used in higher volumes than other categories. Due to the high volume of water used for processes, the share of the true cost associated with process water also tends to be high. However, processes such as the chiller and dehumidifier system in the fiberglass manufacturing facility show how the share of water volume can seem low (3%) but can have a more significant impact (21%) on the true cost of water for the facility. Similarly, the breakdown of the true cost of water by cost component clearly shows how a significant part of the cost can be associated with expenditures other than water acquisition, such as water pumping and wastewater treatment. Table 4.1 summarizes results of applying the PWP tool to the three facilities.

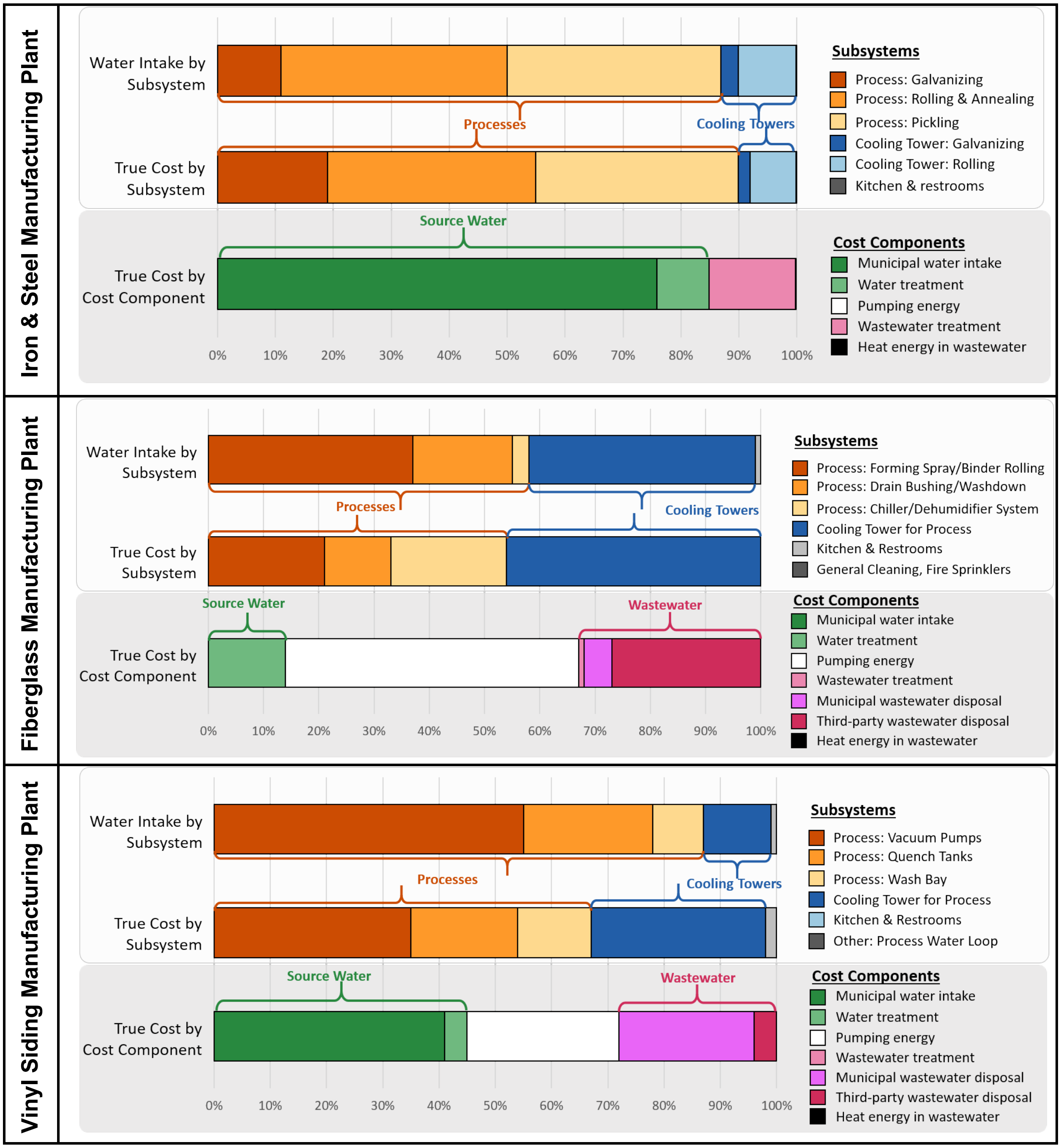

Figure 4.1 Water use and true cost by subsystem and cost component for three facilities using PWP tool

Figure source: Malhotra et al. 2021

Table 4.1 Summary of Pilot Water INPLTs

Source: Malhotra et al. 2021

	Pilot training 1	Pilot training 2	Pilot training 3
No. of participants	20	10	11
Industry type	Iron and steel	Fiberglass	Vinyl siding
Plant boundary	Cold mill	Entire plant	Entire plant
Main water-using subsystems	Cooling towers, processes (cooling and washing)	Cooling towers, process (RO water), cleaning	Process, cooling towers, cleaning
Intake water source	Municipal water (also, river water for other areas of the plant)	Groundwater	Municipal water
Discharge outlets	River, on-site lagoon	Municipal sewer, industrial sewer	Municipal sewer
Source water use	0.45 m^3/tonne (0.12 kgal per metric ton production)	2.2 m^3/tonne (0.57 kgal per metric ton production)	2.6 m^3/tonne (0.33 kgal per 1000 lb production)
True cost of water	\$1.55/m^3 (\$5.88 per kgal, 1.32 times direct cost)	\$1.71/m^3 (\$6.48 per kgal, 3.15 times direct cost)	\$2.12/m^3 (\$8.01 per kgal, 1.45 times direct cost)

4.3.2 Opportunities and Future Work

There are numerous opportunities for facilities to improve their water efficiency and/or associated costs to reach their sustainability goals or reduce water-related risks. Corporations can benefit from defining clear goals and desired outcomes in any sustainability-related effort. The PWP tool has helped facilities examine water use and true cost at the subsystem level and identify areas of greatest opportunities for improvement. Depending on the priorities of each facility, selecting from a list of process improvements with different potential outcomes may be required. For instance, there may be facilities exposed to regional water scarcity that want to reduce their intake water and discharges at the expense of increased energy use due to on-site wastewater treatment for recirculation.

The importance of metering and submetering is highlighted throughout this report. Facilities can benefit from creating a water management plan that includes water use at the facility level, including self-supplied water. Submetering water use for specific processes is also crucial for planning improvements and optimizing resources. In cases where water use data are already collected, it is important to emphasize the value of adequate data management practices that support facilities in extracting useful information to make informed decisions.

There are diverse opportunities for facilities to apply advanced technologies for data management that can help optimize resources within a facility. These technologies include advanced water meters, smart water quality sensors, Internet of Things (IoT) technologies that use networks of connected water quality or flow sensors, dashboards with data aggregation and visualization, and supervisory control and data acquisition (SCADA) systems that collect real-time data supporting smart decision making and improving efficiency.

While there are multiple opportunities to improve water efficiency in a manufacturing facility, Section 4.3 highlights the importance of assessing the true cost of water. The nominal cost paid by facilities to acquire water partially reflects the cost of using water as a means of production. Measuring all the costs associated with water use can help identify cost-intensive operations in which optimizing water use can yield significant financial returns.

4.4 Advanced Strategies, Including Those from Other Areas/Disciplines

4.4.1 Within the Fenceline

4.4.1.1 Water Use Substitution/Efficiency

Section 4.4.1.1 Summary

- As an example of a "dry" or water-less technology, this section compares the life cycle impacts of gas-based metalworking fluids with water-based metalworking fluids based on their functional performance reported in the literature.
- Gas-based metalworking fluids show significantly improved tool life (between 2–100 times) but have a higher life cycle primary energy and water use than water-based fluids.
- Higher life cycle energy and water use are a direct consequence of two practices. First, gas-based metalworking fluids are often applied like their water-based counterparts—by flooding the tool-workpiece interface with the gas. This leads to significant waste of industrial gasses, which have very energy- and water- intensive upstream production processes. Second, tool life improvement is prioritized over increasing volumetric throughput (i.e., machining faster, particularly in bulk material removal operations) despite some experiments showing that throughput could be increased without equivalently compromising tool life.
- Life-cycle energy and water use of gas-based substitutes for water-intensive industrial processes can be reduced through optimization and/or targeted delivery of gasses when used in an open loop and through closed-loop operation of the gas whenever technically feasible. When used judiciously, gas-based technologies can not only dramatically reduce on-site water use, but may potentially provide other environmental and occupational health benefits.
- Elements of this section draw from the following work published by report authors: Rao, Sholes and Cresko (2019) and Supekar et al. (2020).

Water use in manufacturing could be reduced or eliminated by implementing new generations of equipment and environmentally friendly technologies based on enzyme products, cryogenics, dry saturated steam, ultrasound, ozone, pulsed lights, and industrial gases. This report collectively refers to such technologies as "dry technologies" or technologies for "dry factories" that may help reduce on-site water use and potentially reduce life cycle water, energy, and chemicals use. An expansive review of dry factory technologies is needed to understand the technical advantages and limitations, life cycle environmental impacts, and process techno-economics of these technologies to identify promising opportunities for dramatically reducing on-site water use and water pollution. Further, tradeoffs in sustainability and economics must be evaluated and understood to ensure that water use sustainability is not coming at the expense of another resource or sustainability criteria or causing an excessive economic burden. This section presents one example of a dry factory technology that uses industrial gases to deliver cooling and lubrication in the machining of metals instead of water-based oil emulsions. In addition to demonstrating the water savings benefit, the authors consider the sustainability tradeoffs associated with dry factories.

The following case study compares energy, water use, and other life cycle impacts of conventional aqueous (water-based) and novel dry (gas-based) metalworking fluids (MWFs) in machining operations. Some of the report authors published this work as a peer-reviewed article in the *Journal of Industrial Ecology* (Supekar et al. 2020). The next section presents select findings from the paper, highlighting the potential performance improvements that may be realized using gas-based "dry" MWFs and discusses factors that drive their environmental impacts and ways to reduce these impacts. (For details about the methods, modeling data and assumptions, and results, see the published article.)

Overview Life Cycle Assessment Goal, Scope, and Functional Unit

Gas-based MWFs, which commonly use industrial gases such as nitrogen, compressed air, and carbon dioxide, have been proposed as alternative coolants and lubricants in machining operations. This substitution could mitigate problems associated with the conventional aqueous MWFs ubiquitous in the metals manufacturing industry, including water use, water pollution, industrial hygiene, occupational health, and performance limitations. In several instances, gas-based MWFs have significantly outperformed aqueous MWFs in terms of cutting tool life, surface finish, and specific cutting energy,[28] although significant variability exists in these metrics in the reported literature. Further, industrial gases are considerably energy-intensive to make and/or transport.

While other researchers have conducted life cycle assessments (LCAs) of different MWFs, Supekar et al. (2020) recognized the need to perform an LCA of MWFs with a scope that incorporates differences in machining performance. This analysis would account for the possibility that improved machining performance may either reduce the machining time required to produce a fixed quantity of machined products or allow greater throughput within a fixed time. The latter is more likely in high-value industries such as automotive, aerospace, and medical devices. The paper authors attempt to bridge this gap in the literature by addressing the following research question: how do the life cycle impacts, particularly the energy and water use, associated with the production, consumptive use, delivery, and disposal of gas-based MWFs compare with aqueous MWFs when considering reported differences in their functional performance in published experimental studies? The focus on energy and water use reflects their close coupling in MWF systems. Water-based MWFs require considerable energy during

[28] Gas-based MWFs have been shown to have a higher penetration into the cutting zone created between the cutting tool and the workpiece. In the case of N_2 and CO_2, rapid expansion from a pressurized state to ambient pressure leads to rapid cooling because of the Joule-Thompson effect. Improved access to regions of friction and heat generation through lower surface tension, along with significantly cooler delivery media in the case of N_2 and CO_2, thus creates the potential for more effective heat removal and lubrication despite lower volumetric heat removal capacities as gases compared to aqueous MWFs.

their use phase, and gas-based MWFs—while water-less in their use phase—require considerable energy and water in their production phase.

Supekar et al. (2020) compared aqueous MWFs with three gas-based MWFs commonly found in the literature: minimum quantity lubricant-in-compressed air (MQL), liquid/gaseous N_2, and liquid/supercritical CO_2. (For a more expansive description of all MWF technologies, see the published journal article.) The authors calculated life cycle impacts using the service provided by a metalworking fluid system over a period of one year as the functional unit, with the quantity of material machined over a year serving as the primary reference flow. This choice of functional unit accounted for the performance aspect of MWFs because MWFs that allow a higher tool life would allow a greater volume of material to be machined over a year. Data from a total of 86 experimental MWF comparisons from 29 studies published between 2001 and 2019 spanning several machining processes and materials were compiled for the analysis. Figure 4.2 shows the system boundaries used in the LCA analysis to calculate life cycle impacts per unit volume of material machined using a given MWF.

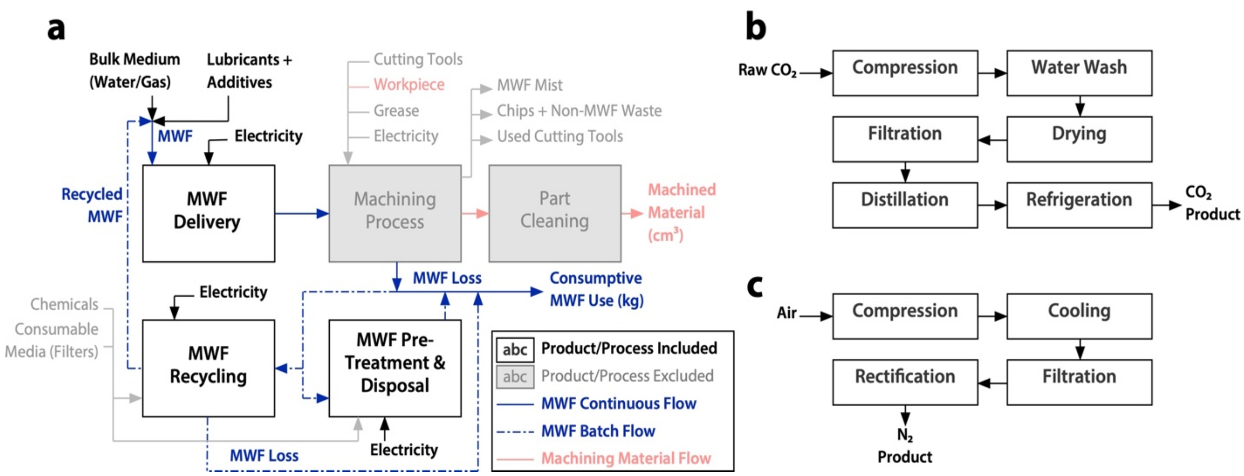

Figure 4.2 System boundaries used to calculate life cycle impacts

(a) System boundary used to calculate the primary energy and water use per unit volume of material machined using aqueous and gas-based metalworking fluids. Dashed lines indicate batch flows that only apply to aqueous metalworking fluids. Overview of the processes used to make (b) liquid CO_2 and (c) liquid N_2.

Figure source: Supekar et al. (2020)

Summary of Key Findings

The analysis showed that despite the reported improvement in tool life with N_2 and CO_2-based MWFs, the electricity- and water-intensive separation and purification processes for N_2 and CO_2 lead to higher primary energy and water use per volume of material machined relative to water-based MWFs (see Figure 4.3). Although MQL was found to have lower primary energy use, significant consumptive water use associated with the vegetable oil commonly used with this MWF leads to higher overall water use than aqueous MWF. Thus, the analysis found that gas-based MWFs, while reducing on-site water use, pollution and several occupational health hazards, shifted water use, energy use, and other environmental impacts upstream of the manufacturing plant.

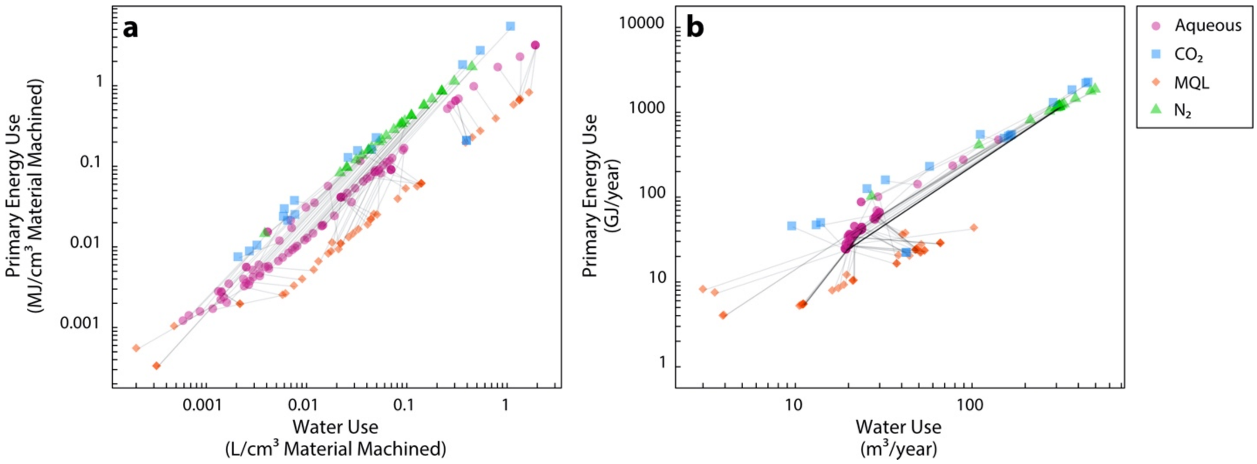

Figure 4.3 Primary energy use and water use associated with the production, delivery, and disposal of MWFs

(a) per unit volume of material machined over a year, and (b) on an annual basis

Figure source: Supekar et al. (2020)

Upon examining the experimental data and comparing machining performance using a statistical technique called "blocking,"[29] the authors found that the tool life with gas-based MWFs was almost always higher than aqueous MWFs. An increase in tool life is anticipated to decrease tool costs and minimize unproductive machine downtime. However, the reported improvements in tool life would not necessarily translate to improving annual throughput because most (> 90%) experiments were set up to compare tool life, keeping the material removal rate (MRR)[30] constant following the conventional practice of comparing MWFs under identical machining conditions (De Chiffre and Belluco 2000). Throughput gains depend on reducing downtime from fewer tool changes due to improved tool life. The rate of tool changes (and downtime for tool changes) diminishes approximately quadratically with increasing tool life (see the paper for details on how this relationship was ascertained). Increasing the MRR

[29] To meaningfully compare MWF performance across studies, we compute the differences in tool life, throughput, and energy and water use per unit volume of material machined across studies using an approach called "blocking" or "pairing" (Box, Hunter, and Hunter 1978). Comparing differences instead of absolute values of these observed variables significantly reduces the effect of confounding factors across studies and increases the precision of the comparison, which allows us to detect meaningful differences between the MWFs even if the magnitude of such differences is small relative to the absolute value of the response variables. However, the data collected from the literature is observational; thus the collective results from experiments cannot be considered as randomized and pooled. While some support exists in the literature for applying "subjective randomization" to non-randomized observational data (Rubin 1974) to allow hypothesis testing, others have cautioned against such an approach, citing inherent sampling biases and Type I errors in significance tests applied to observational datasets (Greenland 1990; Copas and Li 1997). In this study, the authors calculated the differences and ratios of the response variables for each pair of MWFs tested in an experiment and reported the medians, mean, and standard deviations without subsequent hypothesis testing. In lieu of significance tests, the authors graphically plotted the differences in energy and water use from the different pairs of MWFs and supplemented the quantitative metrics with a qualitative discussion in the context of the research question.

[30] Material removal rate is the volume of material machined in a certain time in conventional subtractive manufacturing processes and is often used to quantify and compare the productivity of a machining process. Generally calculated as the product of the axial depth of cut, radial depth of cut, and the cutting speed, MRR is also used to determine the machining power needed to cut a given material, which, in turn, determines the selection or design of the appropriate machine tool and spindle.

(typically through higher cutting speeds), without compromising much or at all on tool life, presents a significant opportunity to increase throughput and, therefore, the life cycle impacts per unit of material machined. The authors found some evidence for this approach in the published literature examined in this study, as shown in Figure 4.4, in which throughput improvements were most pronounced (darker circles) either when tool life was increased by several minutes using gas-based MWFs from an aqueous MWF baseline of about 3–7 minutes or when the MMR (circle size) was increased by 2–6 cm^3/min.

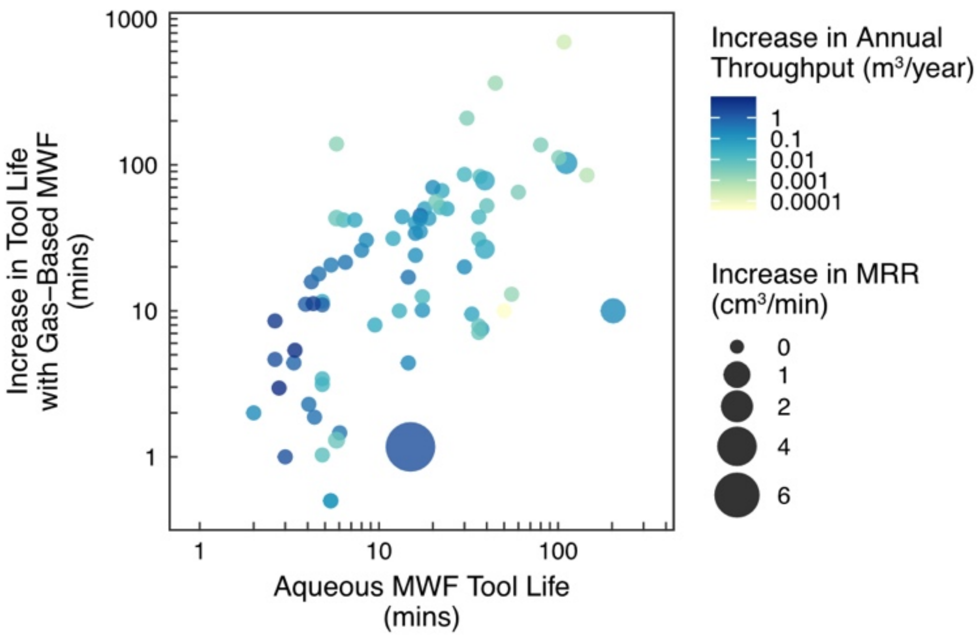

Figure 4.4. Reported increases in tool life with gas-based MWFs

Reported in the literature, shown as a function of the corresponding aqueous MWF tool life and increase in MRR within a given experiment (assumes a tool change time of 1 minute)

Figure source: Supekar et al. (2020)

A sensitivity analysis of the LCA results revealed that tool change time and machine utilization factors have the largest impact on the primary energy and water use of aqueous MWFs, although they do not affect the primary energy and water use of gas-based MWFs. This is because both these parameters affect the production time of the machine tool, and because gas-based MWFs operate in an open loop, any changes in the production time affect the throughput and annual primary energy/water use in the same proportion. In contrast, aqueous MWF has a fixed consumptive use component from daily evaporative losses and periodic filtration that is practically unaffected by production time. Therefore a decrease in production time would lead to higher primary energy and water use for aqueous MWF than in the nominal scenario. Primary energy and water use of aqueous MWF is also sensitive to the daily MWF make-up and MWF filtration frequency during maintenance, which are parameters that contribute most to consumptive use. Gas transportation distance has a larger impact on the primary energy and water use of CO_2 MWF than N_2 MWF, since production of N_2 comprises a larger proportion of the total MWF impact than CO_2.

Conclusions and Outlook

Primary energy and water use of gas-based MWFs could be reduced by focusing on achieving higher MRRs and throughput compared to aqueous MWFs instead of solely targeting improvements in tool life. The authors identify two main approaches for reducing the primary energy and water use of gas-based MWFs within the scope of the analysis. The first applies particularly to CO_2 and N_2 MWFs. It involves increasing cutting speeds to achieve significantly higher MRRs than those allowed by aqueous MWFs by exploiting the potential of these gases to deliver more effective cooling and lubrication. Increasing the MRR without significantly compromising on tool life and dynamic stability of the machining process can lead to substantial increases in throughput. This increase, in turn, would reduce the primary energy and water use per unit of material machined.

To break even with the primary energy and water use per unit of material machined with aqueous MWF, CO_2 and N_2 MWFs would have to increase their throughput by the ratios shown in Figure 4.5, assuming flow rates and delivery pressures remain unchanged. For instance, in one study, a roughly 25% improvement in MRR with CO_2 MWF over aqueous MWF (while maintaining MWF flow rates/pressures) would lead to identical primary energy use per unit of material machined for both MWFs (Sadik et al. 2016). In other work, however, nearly six-fold increases in MRR would be needed for CO_2 MWF to equal aqueous MWF in its primary energy use (Stephenson et al. 2014). Experimental exploration of whether such leaps in throughput via increased MRR may be possible by modifying machining parameters or tool geometries is scant in the literature, and this presents a significant opportunity for future work to understand the potential of gas-based MWFs.

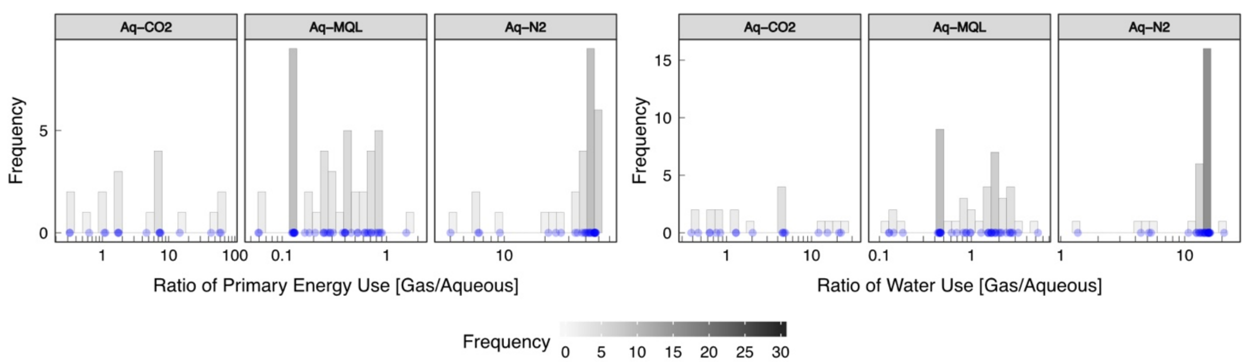

Figure 4.5 Ratios of primary energy use (left) and water use (right) for gas-based and aqueous MWFs

Ratios correspond to the differences in paired or "blocked" data, where a ratio of 1 indicates that the primary energy or water use for the gas-based MWF is equal to that of the aqueous MWF in a given paired experiment. Blue dots represent ratios in primary energy and water use in individual experiments on which the histograms in the figure are based.

Figure source: Supekar et al. (2020)

The second approach involves optimizing the delivery of gas-based MWFs to precisely meet the needs of the specific processes in which they are used. In particular, CO_2 and N_2 MWFs reported in the literature are primarily delivered by flooding the tool-workpiece interface with the gas without considering how much gas would achieve effective cooling and lubrication. Studies show that higher gas flow rates yield diminishing returns in improving tool life beyond a certain point (Skerlos et al. 2008; Bermingham et al. 2012; Sadik et al. 2016). The direction and point of applying gas-based MWFs is also critical to their performance (Marksberry and Jawahir 2008), and care must be taken not to starve the tool-workpiece interface, which might result in catastrophic tool failure and/or workpiece damage due to sub-optimal nozzle placement, direction, or geometry.

Understanding how to minimize consumptive flows of energy-intensive CO_2 and N_2 gases while improving machining throughput compared to aqueous MWFs presents another significant research opportunity. This research would include exploring through-tool delivery of the gases (Sorbo and Dionne 2014; Tahri et al. 2017). Another delivery optimization strategy for CO_2 and N_2 MWFs would increase their delivery pressure. Both CO_2 and N_2 rely on the Joule-Thomson effect[31] to provide a jet of low-temperature gas to cool the tool-workpiece interface. Given that compression energy during the use phase contributes to less than 2% of the total embodied primary energy of N_2 and CO_2 MWFs, expanding the gases from a higher pressure may facilitate higher heat removal and higher tool life (Mulyana, Rahim, and Yahaya 2017; Supekar et al. 2012).

While not considered in this study, system expansion to include cutting tools and machine tool energy consumption in particular may substantially affect the comparative results for net primary energy use of aqueous and gas-based MWFs, depending on the process. Chips and finished parts machined with gas-based MWFs are also largely free of substantial oily residues seen with aqueous MWF materials, and this can further reduce costs and primary energy and water use associated with post-machining cleaning.

Finally, although gas-based MWFs shift water use upstream of the manufacturing facility to thermoelectric power use (> 80% of U.S. generation) for gas separation and purification electricity use steps in the case of N_2 and CO_2 and irrigation in the case of vegetable oil used in MQL, the environmental implications of water use in a factory (direct use) and water use upstream (indirect use) may be quite different. Aside from differences in types and levels of pollutant loadings associated with thermoelectric power generation and process water use, differences in potential water stress that may be created by direct and indirect water use in the context of metals manufacturing (Rao, Sholes, and Cresko 2019) are worth considering when comparing the relative environmental merits of gas-based and aqueous MWFs. It is also worth noting that as the share of renewables in electricity supply increases, the indirect water use (consumptive and overall) from electricity use for CO_2 and N_2 MWFs may further decrease relative to aqueous MWFs.

Perspectives on Developing Dry Factories Technologies

As elucidated by the metalworking fluids case study in the previous section, the use of water-less or water-lean technologies in water-intensive processes can not only dramatically reduce on-site water use but may also potentially provide other environmental and occupational health

[31] The Joule-Thomson effect (also known as the Joule-Kelvin or Kelvin-Joule effect) is a thermodynamic concept describing the temperature change occurring when a real gas is forced through a porous plug or valve that is insulated such that no heat is exchanged with the environment. At room temperature, most gases (excepting neon, helium, and hydrogen) cool upon expansion when being throttled through an orifice via the Joule-Thomson process.

benefits when used appropriately. Other applications of dry technologies include CO_2-based cleaning of semiconductor chips (Supekar and Skerlos 2014a), surface cleaning using laser ablation (Zhou et al. 2002), and CO_2-based power cycles (Ahn et al. 2015). It is likely that the replacement working fluid or active functional agent(s) behind dry factory technologies, such as industrial gases in the case of metalworking fluids, would have significant economic and environmental burdens of their own. It is, therefore, imperative that as these novel technologies are researched, developed, and deployed, researchers consider the following sustainable design principles adapted from Skerlos (2015).

To be adopted, technology solutions must solve significant problems, addressing an unmet and important environmental or social challenge. Dry factories technologies address the need to alleviate water stress in the face of global environmental change. In the metalworking fluids case study, unmet challenges also included reducing highly polluted wastewater streams with significant metals and BOD loadings and decreasing severe health hazards for machinists who have prolonged exposure to microbes and chemicals present in traditional water-based formulations. It is also essential to consider the magnitude of change in environmental and/or social impact the technology brings about. Incremental changes in performance, while important and certainly useful, may not be sufficient to address the larger challenges the technology aims to solve.

Next, researchers must consider whether over its life cycle the technology might lead to undesirable environmental or social consequences that may overshadow its benefits. In the case of gas-based metalworking fluids, the analysis showed that the upstream energy use for gas separation and purification may lead to a tradeoff between reducing the on-site water footprint and increasing the life cycle energy footprint. While it may not be possible to reduce the primary energy footprint beyond a certain point, the climate and air quality impacts from fossil fuel-based energy sources could be reduced by switching to low-carbon and renewable sources of electricity and heat in the upstream gas production facilities. On the other hand, gas-based metalworking fluids would increase reliance on the industrial gasses supply chain. Quantifying such environmental and social tradeoffs using life cycle assessment or other methods is therefore crucial to the success of dry technologies.

Researchers then need to *consider whether the technology will likely be adopted and self-sustaining in the market.* A technology may reduce the water footprint of a manufacturing process while creating fewer environmental or social tradeoffs, but its efficacy would only be realized if the technology is adopted at a meaningful scale. While technology scale-up depends on several technical and non-technical factors, successfully scaled-up technologies create significant value for their adopters (Lindsey 1998; Skerlos 2015; Maccioni, Borgianni, and Pigosso 2019). Value creation can be achieved by adding positive value, for example, through innovation and strategic/niche markets with a higher willingness to pay or higher consciousness of environmental and social impacts. Removing negative value is another way of creating value, for example, by reducing production costs, regulatory losses, litigation expenses, and damage to public image. Innovation is undoubtedly necessary for creating value in the case of gas-based cutting fluids and other dry factories technologies. Studies have consistently shown that gas-based metalworking fluids support better MRRs, tool life, and part quality, thereby creating a competitive performance advantage. Concurrently, the resulting prevention of water pollution and reduction of diseases in machine tool operators can reduce manufacturing and health care costs. Quantifying the broader value of a dry factory technology is thus crucial to its successful adoption.

Finally, researchers must pay attention to whether a technology's innovative and market success may lead to unusual increases in consumption of its services or products, a phenomenon known as the *rebound effect*. Significant rebound effects may render the technology less effective in addressing the environmental and/or social challenge it targeted. For instance, the case study demonstrated the performance improvements made possible by using CO_2-based metalworking fluids instead of water-based metalworking fluids. However, in a future where a circular carbon economy—based on technologies that capture, reuse, and/or sequester CO_2—becomes a reality, it is conceivable that the demand for CO_2 could rise substantially. In this scenario, it is probable that the demand for CO_2 as a commodity would make CO_2 a driving economic co-product instead of a waste byproduct in multi-output processes such as ammonia and bioethanol production (Supekar and Skerlos 2014b). As such, the carbon footprint of this commodity CO_2 would change considerably, which could negate some of the carbon benefits that CO_2-based dry factory technologies are expected to provide. It is worth noting that a large market for an alternative technology would also expand supply, lowering the technology's costs.

4.4.1.2 On-site Water Reuse

Section 4.4.1.2 Summary

- This section develops an analytical framework for understanding when the tradeoff between energy and increased on-site manufacturing water reuse is beneficial.
- Based on available data, the primary metals subsector is typically already treating contaminants to a level sufficient for reuse. Excepting total suspended solids, a majority of observations for contaminants in the petroleum and coal products subsector also meet water quality requirements for reuse. These two subsectors have a high potential to realize water savings and resilience benefits of reuse at minimal added cost.
    - One key research and development opportunity relates to improving the treatment of total suspended solids, which would allow for more on-site water reuse.
- Better data to illuminate the relationship between energy and water in the context of on-site manufacturing water reuse would allow manufacturers to improve resilience and lessen their footprint on local watersheds.
- Elements of this section draw from the following work published by report authors: Fuchs and Rao (2021).

Water reuse is a commonly investigated strategy for reducing water use and thereby increasing resilience. However, when a facility treats water on-site for reuse, it increases energy consumption (and associated costs) to reduce water use (and costs). Understanding this tradeoff can help manufacturers identify beneficial reuse opportunities.

This section is adapted from a *Journal of Industrial Ecology* peer-reviewed article by Fuchs and

Rao (2021) (publicly available here), who propose a theoretical, analytical framework comparing the energy required for single use of water to that for on-site reuse in order to study the energy tradeoffs of on-site water reuse from a life cycle perspective. The aim was to develop a simple quantitative metric that answers the following question: for a given manufacturing facility/process, when is it energy beneficial to implement on-site water reuse to replace single use of water (i.e., the energy required for on-site reuse is less than the embedded energy of new water)? Such a metric can help manufacturers and the research communities supporting them identify the energy implications of reuse from a life cycle perspective. Note that this framework ignores the energy required to use the water within the facility (e.g., circulating pumps) because these energy requirements will be the same whether the water is used once or reused.

The energy requirement for a single use of water per unit volume ($E_{tot,single\ use}$) is a function of the energy required to bring clean water to a manufacturing facility and safely discharge it after use. It can be calculated using Equation 5:

$$E_{tot,single\ use} = E_{w,ex} + E_{w,tr} + E_{w,dist} + E_{wwt,comp} + E_{wwt,con} + E_{wwt,tr} + E_{wwt,dis}$$

Equation 5

Where:

$E_{w,ex}$ = energy per unit volume for freshwater extraction to off-site water treatment plant; dependent on source water characteristics such as: depth to water (zero for surface water sources), conveyance distance, pipe friction factor and diameter, volume flow rate, and other parameters

$E_{w,tr}$ = energy per unit volume for freshwater treatment to clean (e.g., potable, recycled) water requirements; dependent on treatment characteristics, such as: quantity and types of contaminants needing to be removed, volume flow rate, temperature, pH, and other parameters

$E_{w,dist}$ = energy for clean water distribution to manufacturing facility; dependent on water distribution system characteristics, such as: elevation gain to facility, distance to facility, pipe friction factor and diameter, volume flow rate, and other parameters

$E_{wwt,comp}$ = energy for treating wastewater on-site to meet compliance requirements before sending to municipal wastewater plant; dependent on characteristics of the treatment process, such as: energy and chemical requirements of treatment technology(ies), and other parameters

$E_{wwt,con}$ = energy for wastewater conveyance to municipal wastewater plant; dependent on municipal wastewater system characteristics, such as: elevation gain to facility, distance to facility, pipe friction factor and diameter, volume flow rate, and other parameters

$E_{wwt,tr}$ = energy for treatment at municipal wastewater plant; dependent on wastewater characteristics, such as: quantity and types of contaminants needing to be removed, volume flow rate

$E_{wwt,dis}$ = energy for treated water discharge; dependent on wastewater system characteristics, such as: elevation gain to facility, distance to facility, pipe friction factor and diameter, volume flow rate

Depending on the water sources utilized and the location of wastewater treatment, the energy requirements expressed by the terms in Equation 5 will be incurred at the facility (‘direct’), outside of it (‘indirect’), or a mixture of both. Direct energy requirements will be the responsibility of the facility, whereas indirect requirements will not (aside from costs passed to the facility by the outside entity). For facilities utilizing only municipal water sources, the energy consumption for $E_{w,ex}$, $E_{w,tr}$, and $E_{w,dist}$, will be indirect. For facilities utilizing only self-supplied sources, these same terms will be direct. In either case, $E_{wwt,comp}$ will be direct. Similarly, for facilities disposing wastewater entirely through the municipal system, $E_{wwt,con}$, $E_{wwt,tr}$, and $E_{wwt,dis}$ are indirect, whereas, for facilities treating wastewater entirely on-site and disposing it to a local water body, these terms will be direct. Other embedded energy, such as the energy required to manufacture treatment chemicals, is indirect and not reflected in Equation 5.

The energy requirement for reuse ($E_{tot,reuse}$) is shown in Equation 6.

$$E_{tot,reuse} = E_{w,ex} + E_{w,tr} + E_{w,dist} + \sum_{i}^{x} E_{reuse,i} + E_{wwt,comp} + E_{wwt,con} + E_{ww,tr} + E_{wwt,dis}$$

Equation 6

Where:

x = number of times water is reused at facility

$E_{reuse,i}$ = energy requirement to treat on-site after i^{th} reuse, either for reuse again or discharge per permit requirements; function of quantity and types of contaminants needing to be removed, volume flow rate, embedded energy in chemicals for treatment

The same characterization of a facility's direct and indirect responsibility for each term in Equation 5 applies to the terms in Equation 6, and $E_{reuse,i}$ is direct. Equation 5 and Equation 6 are identical except for the inclusion of energy requirements for reuse in Equation 6. Reuse becomes energy beneficial when the treatment requirements for the i^{th} reuse of water is less than $E_{tot,single}$ use. More generally, reuse is energy beneficial when:

$$\frac{\left(E_{tot,reuse}/_{x}\right)}{E_{tot,single\,use}} < 1.$$

Equation 7

In Fuchs and Rao (2021), the initial research approach centered on discovering manufacturing processes for which the following necessary parameters could be identified:

- Input to on-site treatment: contaminant mix, water flow rate, and concentration after reuse (contaminant concentration will increase with every reuse cycle).
- On-site treatment process: energy intensity of on-site treatment process, number of times water can be reused, chemical requirements.
- Output from on-site treatment: water quality (contaminant concentration) requirements for reuse, (fit-for-use), water flow rate requirement for reuse.

Except for $E_{reuse,i}$ and $E_{wwt,comp}$, the terms in Equation 6 can be estimated using publicly available data (Elliott et al. 2003; EPRI 2002; EPRI 2013; Navigant Consulting, Inc. 2006; NYSERDA 2008). However, the current understanding of $E_{reuse,i}$ is poor; it requires more insight into manufacturing wastewater contaminants, their concentrations and potential interactions, and the treatment trains needed for this effluent to be of sufficient quality for reuse. Table 4.2 displays several categories of data gaps that must be filled to better understand the energy-water tradeoffs associated with water reuse; note that Sections 2.3.1 and 2.3.2 further discuss the categories in the first two rows of this table.

Table 4.2. Data Required for Tradeoff Analysis of Manufacturing Water Reuse

Category	Available data	Desired data
Contaminant mixes	EPA DMR and TRI data; case studies; EPA Effluent Guidelines	Mixes for smaller manufacturing plants not required to have NPDES permits; mixes in effluents sent to POTWs
Flow rates of effluent	Several case studies contain process flows	Effluent discharges by disposal locations (*e.g.*, POTW, surface water)
Water quality requirements for manufacturing uses	Parameters for pulp & paper, chemical, petrochemical, and textile subsectors, plus recirculating cooling systems (Rommelmann et al. 2004)	Data for other manufacturing subsectors
Treatment technology effectiveness	EPA IWTT database; several case studies	In-situ performance data
Energy requirements for treatment	Ranges compiled from literature review	In-situ performance data that ideally encompass embodied energy

$E_{tot,reuse}$ in Equation 7 will be a function of the treatment technology utilized. Figure S1-5 from Fuchs and Rao (2021), presented as Figure 4.6, categorizes common treatment technologies. The first tier of the figure (with tiers reading from left to right) classifies technologies by primary mechanism: physical, chemical, and biological. The second tier displays categories encompassing the examples of individual treatment technologies shown in the third tier. This figure is not meant to be exhaustive, but to reasonably represent the universe of treatment technologies that can be applied at scale. Classifying them by mechanism helps determine their energy requirements by facilitating a better understanding of how energy is used to remove contaminants. For example, physical separation processes use energy to physically remove contaminants from wastewater. Note that this categorization is not definitive, and some lines between categories are blurred. For example, it would be accurate to consider certain chemical and physical technologies as being at different points along a physicochemical spectrum.

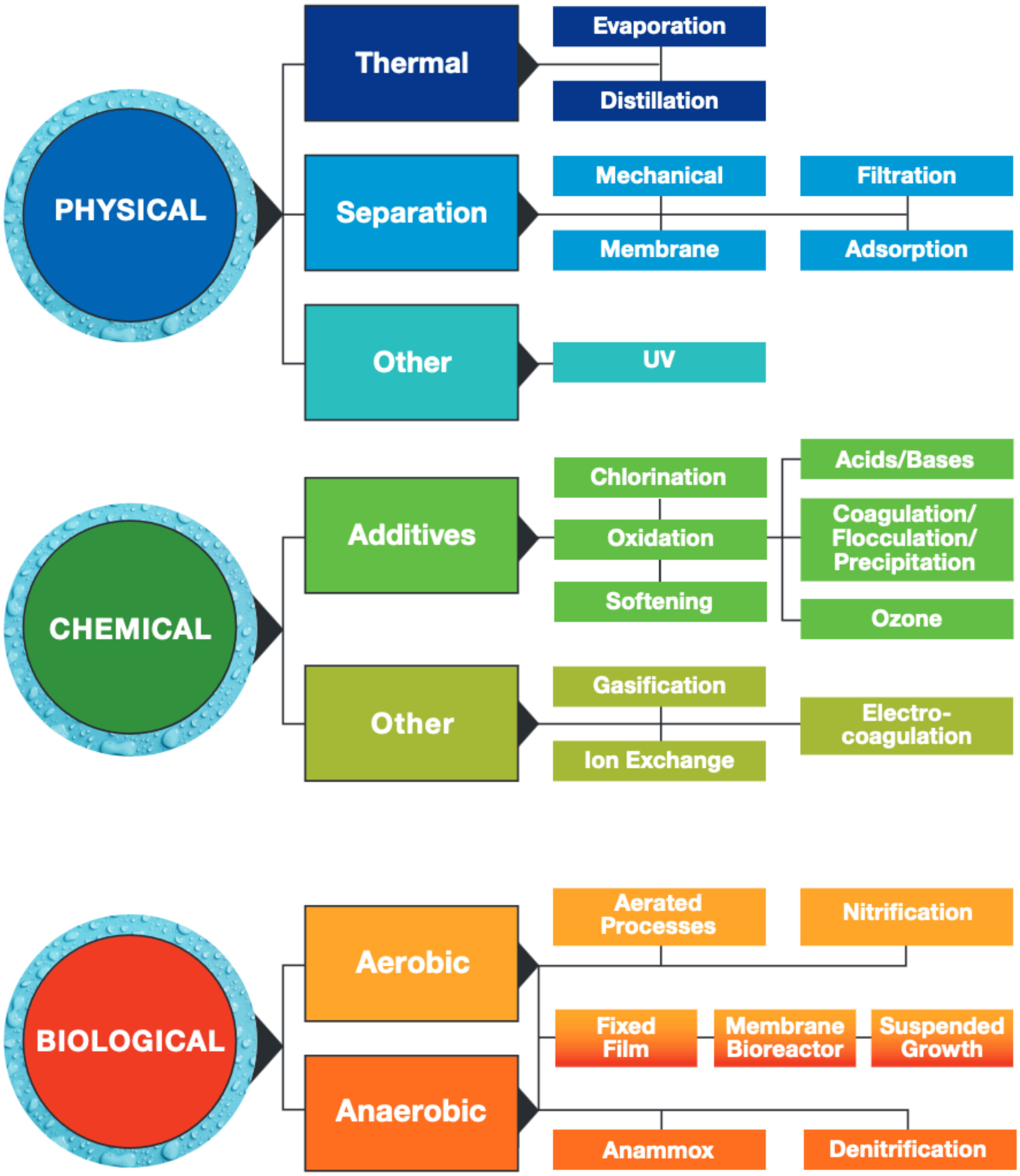

Figure 4.6. Categorization of treatment technologies by primary mechanism

Figure source: Fuchs and Rao 2021, Figure S1-5

The publicly available data do not allow for comprehensively applying the proposed framework due to insufficient information on wastewater contaminants and treatment technology energy intensities. However, the data on discharges to surface waters from DMR permits can be compared to contaminant- and subsector-specific water quality requirements shown in Table 4.3. This table synthesizes information from the two most comprehensive sources available, for five separate manufacturing subsectors. Because quality needs are process-dependent, this table should be interpreted as broader guidance instead of specific goals for treatment for every process within listed seubsctors. For more information and to see water quality requirements for recirculating cooling systems and boiler feedwater (by pressure), refer to Table 2 in Fuchs and Rao (2021).

Table 4.3. Summary of Water Quality Requirements for Reclaimed Manufacturing Water by Manufacturing Subsector

Contaminant	Chemical	Petroleum & Coal Products	Primary Metals	Pulp & Paper	Textiles
Metals					
Calcium (Ca)	68	75	-	20	-
Copper (Cu)	-	0.05	-	-	0.01–0.05
Iron (Fe)	0.1	1.0	-	0.1–1.0	0.1–0.3
Magnesium (Mg)	19	30	-	12	-
Manganese (Mn)	0.1	-	-	0.05–0.5	0.01–0.05
Others					
Chloride (Cl)	500	300	500	200–1000	-
Bicarbonate (HCO_3)	128	480	-	-	-
Nitrate (NO_3)	5	10	-	-	-
Silica (SiO_2)	50	60	-	50	-
Sulfate (SO_4)	100	600	-	-	-
Dissolved solids (TDS)	1000	1000	1500	100	100
Suspended solids (TSS)	5	10	3000	10	5
Hardness ($CaCO_3$)	250	350	1000	100–475	25
Alkalinity ($CaCO_3$)	125	500	200	-	-
Color	*20*	*25*	*-*	*10–30*	*5*
pH	*5.5–9.0*	*6.0–9.0*	*5.0–9.0*	*4.6–10.0*	*6.0–8.0*

Values are in mg/L except color [color units] and pH; original sources are DOI (1981) and Rommelman et al. (2004)

If this effluent already meets inlet water quality requirements, manufacturers could theoretically reuse it on-site with little expense beyond new piping. The inequality in Equation 7 would thus be less than one, where reuse is energy beneficial. Building upon this assumption to identify subsectors/processes with a high likelihood of energy beneficial reuse opportunity would consequentially be conservative, serving as a floor of this opportunity.

The authors mapped water quality requirements to DMR data as summarized in Figure 4.7, which displays the statistical distribution for each contaminant by manufacturing subsector as boxplots. Given the wide variation in reported concentrations in the DMR data, these values were indexed to the water quality requirement by dividing each of the former values by the fixed latter value; where a range for water quality exists rather than a single value, only the value for the higher quality requirement (i.e., at the low point of the range) is used, to be more conservative regarding identifying reuse opportunities. The number of observations in the DMR data varies by contaminant and subsector, with a mean of 201. Any contaminant with fewer than 10 occurrences was excluded from this analysis. The maximum number of observations is 1,482 for total suspended solids in the chemical subsector.

Figure 4.7 shows that the primary metals subsector is generally already treating contaminants for which water quality threshold data exist to a level sufficient for reuse, with the share of records where the index value is at or below one ranging by contaminant from 91%–100%. Excepting total suspended solids, more than 60% of observations for contaminants in the petroleum and coal products subsector meet water quality requirements for reclaimed water. This implies that these subsectors have a high potential to realize the water savings and resilience benefits of reuse at minimal added cost. Conversely, the textiles and pulp and paper subsectors would require higher adoption of new treatment technologies to harness the advantages of reuse. Looking at contaminants across subsectors, all occurrences of total residual chlorine fall well below reclaimed water quality requirements—likely a function of stringent limits on chlorine for surface water discharges reported in DMR. Nitrogen, copper, and magnesium are also removed to suitable levels for reuse for more than 80% of the permits reviewed, while iron and alkalinity meet water quality requirements in fewer than one-third of observations.

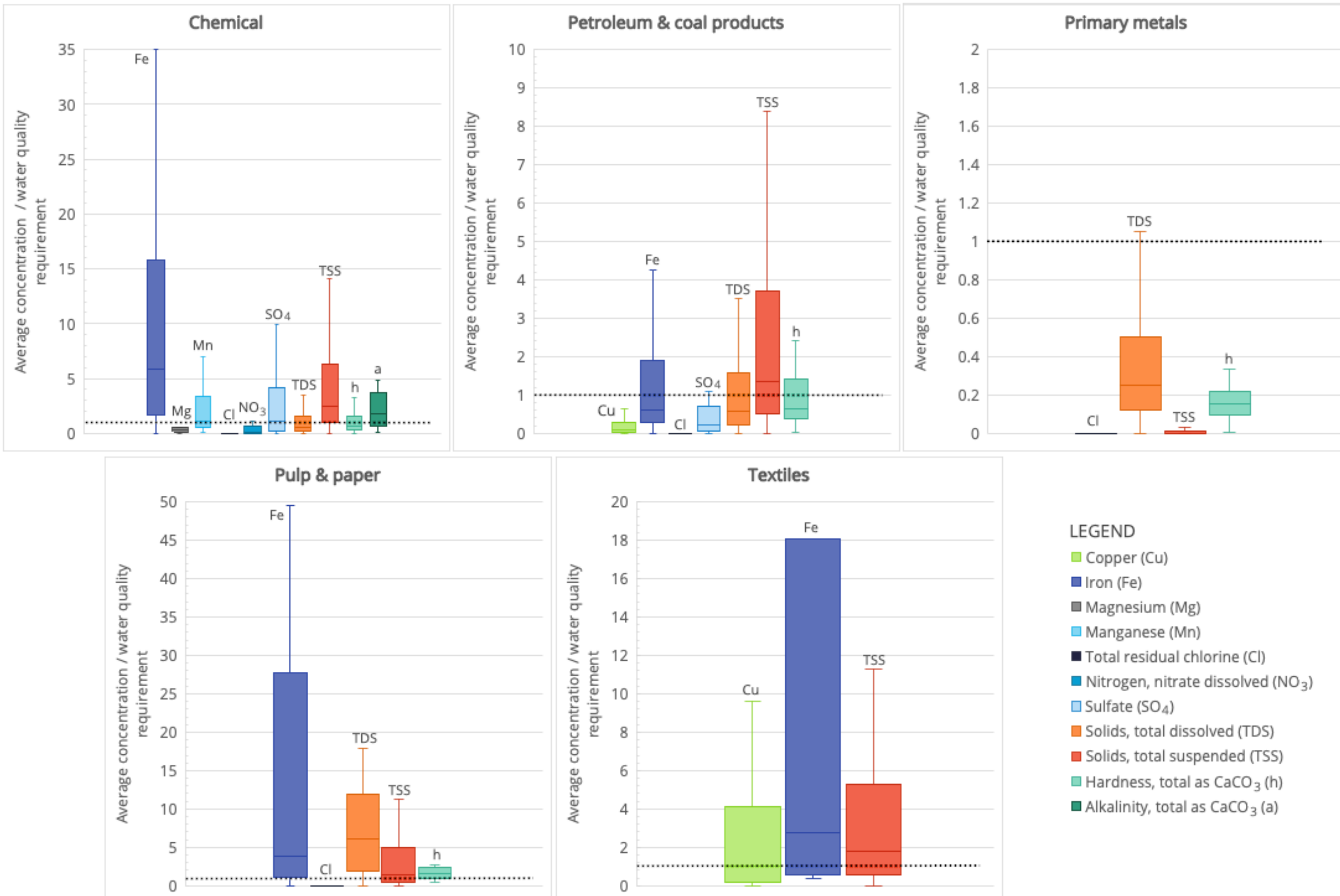

Figure 4.7. Distribution of average concentration of selected contaminants in five manufacturing subsectors

2016 EPA DMR data, indexed to water quality requirements, dashed line at index value of 1

Figure source: Fuchs and Rao 2021

Ultimately, these results illustrate an approach to estimating reuse potential that would be more rigorous given richer, representative data. Note that these results do not apply to any specific facility. Instead, they illustrate how available DMR data on particular contaminant concentrations compare to water quality requirements, thus suggesting the variable potential for reuse by subsector. In these cases, raising awareness about the water reuse benefits and alleviating perceived risks would help realize some cost-effective industrial water reuse potential. It would be beneficial to collect data from or on manufacturers regarding the cost of supply water, flow rates, critical treatment needs (e.g., recalcitrant organics, salt-handling capabilities with an economical sink [Oppenheimer et al. 2016]), and process water quality requirements beyond those presented here. So, too, would be going beyond energy-beneficial reuse to incorporate consideration of the GHG emissions implications of reuse, as pretreatment and treating byproducts for disposal consume energy, and processing treatment byproducts such as sludge can often release methane and nitrous oxide. Also important to consider are the water needs of communities downstream of the manufacturing facility that rely on its return flows. Greater reuse will lessen the availability of water for community use, assuming that return flows are reduced more than withdrawals. A water user could presumably reduce water withdrawals at a rate similar to the reduction in return flows, although this may not always be the case, particularly when production increases. Before implementing reuse at any scale, a water balance should be performed to ensure adequate water supplies at any given time for any community reliant on the same water.

4.4.2 Outside the Fenceline

4.4.2.1 Framework for Determining Optimized Embedded Energy, Greenhouse Gas Emissions, and Resilience for Manufacturing Water Supplies with a Case Study

Section 4.4.2.1 Summary

- This section develops an optimization framework for determining the manufacturing water supply portfolio by estimating tradeoffs between water resilience, energy consumption and embedded GHG emissions in a U.S. region. The method includes understanding regional manufacturing water withdrawals, hydrological conditions, and energy requirements, and the GHG emissions associated with procuring and treating water via sources such as municipal, surface, and groundwater supply.
- The optimization framework outlines multiple scenarios focused on baseline energy usage, lowest energy consumption, and resilient county or facility (based on restricting water withdrawals from a single source below certain thresholds). Finally, it conducts sensitivity analyses to understand the tradeoffs between energy usage and water withdrawal from multiple sources to remain more resilient to water-related risks.

Manufacturers primarily draw water required for their operations from three sources: municipal water, self-supplied surface water, and self-supplied groundwater. The sources of self-supplied water withdrawal in the manufacturing sector are far from balanced: surface water amounts to approximately 80% of self-supplied industrial water, while groundwater accounts for the remaining 20% (Rao et al. 2015). In some regions, over-reliance on surface water may prove costly during droughts and arid periods, with river flows and lake levels declining to levels that cannot sustain the demand for manufacturing water. At that point, plants that have access to groundwater may shift toward more groundwater use, thereby overdrawing it in an unsustainable way (Konikow and Leake 2014). Another consideration is the GHG emissions from the water/wastewater network attributable to the water-energy nexus, specifically through pumping (extraction and distribution) and treatment. The magnitude of GHG emissions embedded in manufacturing water supplies is an unknown but critical issue because the increase in GHG emissions exacerbates global warming, water stress, and intense rainfall events. A 1°C increase in atmospheric temperature increases the water vapor content in the atmosphere by 7% (IPCC 2014). Subsequently, it intensifies atmospheric moisture demand from the land and water bodies, which is satiated through increased evaporation from water bodies and increased evapotranspiration from soils and vegetation (Vano et al. 2014; Seneviratne et al. 2010). This result creates an inexorable feedback loop that will only worsen, especially in regions that will experience significant rainfall deficits. Considering this context, manufacturing facilities must diversify their water supply portfolios to provide resilience against climate change-induced risks, while also assuring that any changes do not come at the cost of increased GHG emissions.

This study develops and examines a simple method to determine an optimum manufacturing water supply portfolio that balances resilience in water supply options and embedded GHG emissions in a given region. Its purpose is to improve the understanding of this balance and its tradeoffs. The method is applied to a case study as a test case. This study does not intend to result in quantitative impacts that can be extrapolated to the entire U.S. manufacturing base.

In the context of this study, *resilience* is considered to be achieved if the manufacturing facility has multiple sources of water and does not overdraw from any single source. The general method developed is essentially a list of the criteria and data needed to understand the optimal mix of water supply sources. The steps are:

1. Develop an understanding of the manufacturing operations in the region of interest. Manufacturing characteristics of interest include the location of the plants (e.g., latitude and longitude coordinates) and water intake volumetric rates by source for each plant.
2. Develop an understanding of the relevant hydrological conditions in the region of interest. This includes the location of municipal water treatment plant(s) (e.g., latitude and longitude coordinates), the location of surface water sources, typical groundwater depths, and elevation changes between water sources and manufacturing plants.
3. Determine the energy requirements to extract, pump, and distribute water in the region and treat water to necessary standards using first principles and published data. Then, establish GHG emissions associated with energy use.
4. Develop a threshold for maximum water withdrawal from any one source using historical information. Historical information could include the historic mix of water supply and known constraints on water sources. This threshold can apply to a given facility or to all the manufacturing facilities in the region of interest collectively, depending on analysis

needs.[32]

5. Calculate the baseline energy and GHG emissions based on the information from steps 1 through 3.
6. Using the threshold(s) identified in step 4, re-calculate energy and GHG emissions for alternate water supply mixes.

The authors applied this analytical method in a case study of Assumption Parish, LA, with the following conditions:

- Manufacturing water withdrawal accounts for >75% of total water withdrawal in the county, thereby ensuring a sufficient number of facilities to analyze.
- Multiple water supply sources exist (surface water, groundwater, public water supply).
- Sufficient data availability on water resources and subsequent energy implications of using those resources.

Figure 4.8(a) breaks down the current manufacturing water withdrawals in the county of Assumption Parish, LA (corresponding to Step 1), and Figure 4.8(b) shows the location of the 11 manufacturing facilities and sole municipal water plant in the county in relation to regional water sources (corresponding to step 2). Currently, 51% of the county's manufacturing water supply is from groundwater, 47% is from surface water, and 2% is from municipal supply (Rao et al. 2017). To estimate the water withdrawals by source and quantity for each facility, county-level estimates for water withdrawal by each manufacturing subsector were evenly distributed to each facility within the subsector and county. This assumption has been made in lieu of any information to disaggregate the county water use to each facility. Distances and elevations between the manufacturing plant and the water sources were determined using GIS. Groundwater depth measurements were available through Assumption Parish (EPA 2020a).

[32] Note that the extent to which future water use trends with historic use data depend upon the changing nature of impacts from climate change and cross-sector competition.

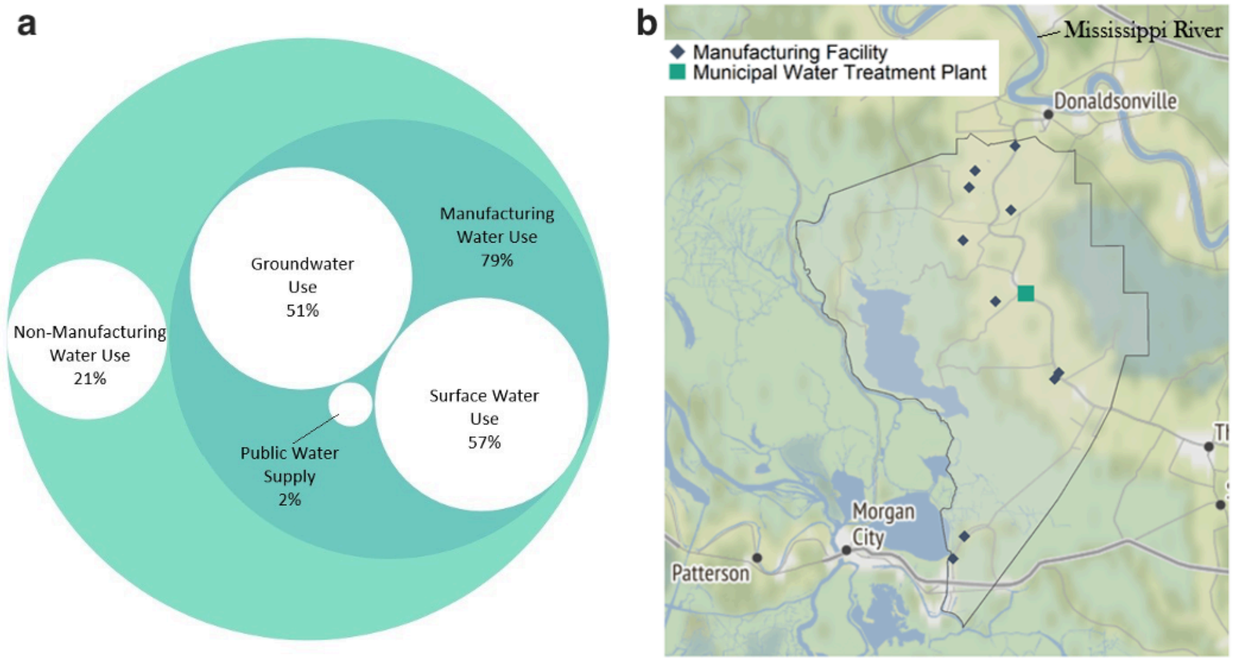

Figure 4.8. Assumption Parish, LA case study

(a) Current manufacturing water withdrawals in Assumption Parish, LA (b) Locations of 11 manufacturing facilities and sole municipal water treatment plant

With Steps 1 and 2 completed, the energy requirements for each source need to be developed (Step 3). Table 4.4 provides the energy consumption used in the calculations for various water withdrawal sources in Assumption Parish. The Energy Consumption column consists of two terms for determining the overall energy requirements for each source. The first term (in kWh/million gallons (MG)) correlates to the energy requirements for raw water treatment for typical freshwater sources on a volumetric basis. The Energy-Consuming Applications column enumerates assumed treatment steps. Municipal water is assumed to be treated to potable water standards, whereas self-supplied ground and surface water is treated to subpotable standards. While this analysis uses a single value, a more robust analysis would include a range of energy requirements based on the contaminant mix and concentration of the water source. The second term (4.5 kWh/MG for each of the three sources) represents the pumping energy requirements per unit of pumping head (ft). This value is developed using first principles (as outlined in Rao et al. 2018) and assumed pump (80%) and motor (87.5%) efficiencies.

Table 4.4. Water Supply Type and Associated Energy Consumption

Water supply type	Energy-consuming applications	Energy consumption	Reference
Onsite surface water	Rapid mixing, flocculation, sedimentation, chemical feed systems, internal pumps, residuals pumping	77 kWh/MG + 4.5 kWh/MG/unit pumping head	(EPRI 2013; Rao et al. 2018)
Onsite groundwater	Chemical feed systems, internal pumps, residuals pumping	26 kWh/MG + 4.5 kWh/MG/unit pumping head	(EPRI 2013; Wilkinson and Kost 2006)
Public water supply	Raw surface water, pumping, rapid mixing, flocculation, sedimentation, chemical feed systems (chlorine disinfection), internal pumps, residuals pumping, non-process loads (buildings, HVAC, lighting, computers)	445 kWh/MG + 4.5 kWh/MG/unit pumping head	(EPRI 2013; Rao et al. 2018)

Applying the energy consumption assumptions from

Table 4.4 to the water utilization trend in Assumption Parish, the water usage optimizations are computed (Figure 4.9). These optimizations are based on the following scenarios:

- **Baseline:** The baseline scenario evaluates current energy use and GHG emissions associated with withdrawing manufacturing water from the respective sources.
- **Scenario 1, Lowest energy:** This scenario calculates the energy/GHG requirements for the lowest energy-consuming water supply mix with no restrictions on how much water is withdrawn from any source.
- **Scenario 2, Resilient county option:** For the entire county, this scenario calculates the energy/GHG requirements for a water supply mix where no more than 40% (average historical groundwater use in Assumption Parish [Prakken and Lovelace 2013]) of the total manufacturing water withdrawal for the county comes from a single source (municipal, surface, or ground).
- **Scenario 3, Resilient facility option:** For each facility, this scenario calculates the

energy/GHG requirements where no more than 40% of each facility's total manufacturing water withdrawal comes from a single source.

Figure 4.9 reveals that the lowest energy usage and GHG emissions (Scenario 1) could be achieved through withdrawing water from a single source (i.e., groundwater). While this is an ideal scenario from an energy usage standpoint, it involves the highest inherent risks of failure due to its overreliance on a single source. An example of a failure mode is aquifer depletion caused by the over-pumping of groundwater and restricting the ability of the facilities to satiate water demand in the future. Moreover, as the groundwater depth increases, the energy required to operate the pump also increases, resulting in higher GHG emissions. The implications are not just limited to the manufacturing facilities; lower groundwater levels, especially in riparian regions, could eradicate vegetation and wildlife ecosystems, escalate land subsidence, and contaminate incumbent groundwater (USGS 2003).

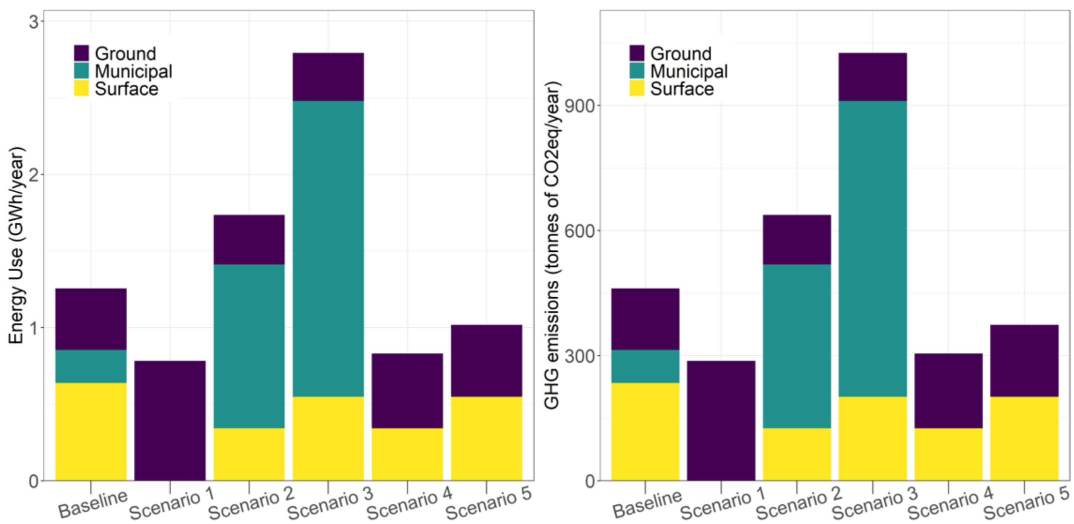

Figure 4.9. Energy consumption and GHG emissions under all scenarios evaluated for Assumption Parish, LA

In the baseline case, annual energy requirements are approximately 1,200 GWh, and GHG emissions are approximately 460 tonnes of CO_{2e}. Values above the figure on the left denote the optimized water supply mix for the scenario. G = groundwater, M = municipal water, S = surface water. Values above the figure on the right denote the change in GHG emissions with respect to the baseline case.

The resilient county scenario (Scenario 2) exhibits higher energy consumption than the baseline and Scenario 1. Meanwhile, the resilient facility scenario (Scenario 3) predicts the highest energy consumption, as it restricts any given facility's water source to a maximum of 40%. The main reason for higher energy consumption is the inclusion of a public water supply at 20% of total water withdrawal in both scenarios. Generally, municipal water supply consumes more energy than the on-site surface and groundwater supply. Embedded energy in the treatment for municipal water supply is typically six and 17 times greater than those of the on-site surface water and groundwater supplies for the same flow and pressure head, respectively (EPRI 2013; Rao et al. 2018; Wilkinson and Kost 2006). This difference reflects water treatment standards: municipal water is generally treated to more stringent standards than self-supplied ground and surface water, although some manufacturing facilities require ultra-pure water beyond the municipal standard.

To further understand water resilience and its energy implications, the study examined two new scenarios that increased the threshold for maximum water withdrawal from any one source:

- **Scenario 4:** For the entire county, energy consumption for a water supply mix where no more than 60% of the total manufacturing water withdrawal (average historical surface water use in Assumption Parish [Prakken and Lovelace 2013]) for the county comes from a single source.
- **Scenario 5:** For each facility, energy consumption for a water supply mix where no more than 60% of each facility's manufacturing water withdrawal comes from a single source.

Scenarios 4 and 5 reduce the energy consumption and GHG emissions considerably because they change the threshold for the maximum amount of water withdrawal for a single source from 40% to 60%. This change eliminates the utilization of municipal water supply, resulting in a significant decrease in energy consumption. However, this criterion is less water resilient as it depends on only two water sources instead of three. This assumption is consistent with the previous scenarios for this county—water resilience comes at the cost of energy consumption and GHG emissions. Therefore, for counties and facilities to achieve water resilience without significantly increasing their energy consumption, the identification of trade-off points is required. Figure 4.10 shows a sensitivity analysis portraying the impact of changes in resilience on embedded energy in manufacturing water for Assumption Parish. As the water use threshold for a single source increases, the resilience decreases, thereby reducing energy consumption and vice versa. For Assumption Parish, the optimum point between water resilience and energy consumption is shown in green text, representing 0.5% energy savings compared to the baseline scenario.

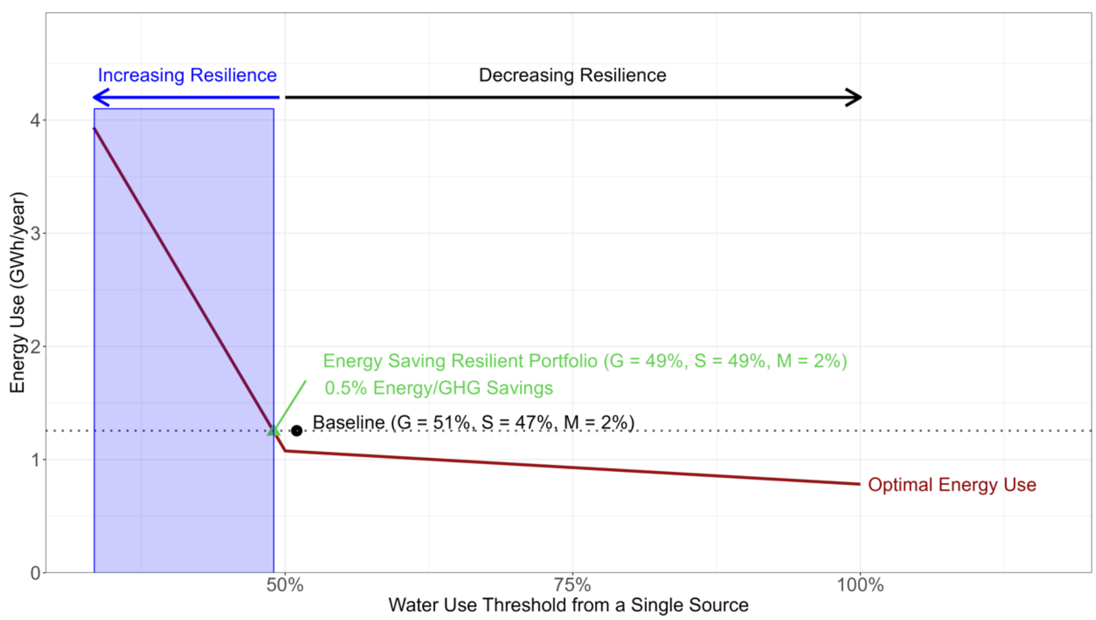

Figure 4.10. Results of sensitivity analysis changing water use threshold for each facility
G = groundwater, S = surface water, and M = municipal water

Determining the energy intensity of groundwater pumping is difficult due to many unknowns associated with groundwater depths and subsurface topologies. The optimal energy usage (red line) in Figure 4.10 is based on the existing groundwater energy intensity of ~800 kWh/MG. To understand the impact of different groundwater energy intensities on the results, the authors performed a sensitivity analysis where the energy intensity varies from 25% to 300% of the values used in Figure 4.10. Within the literature, reported groundwater pumping energy intensities ranged by a factor of about three times (Stokes-Draut et al. 2017).

Figure 4.11 shows the results of this sensitivity analysis: changing groundwater intensities creates a shift in the absolute energy consumption across water-use threshold percentages.

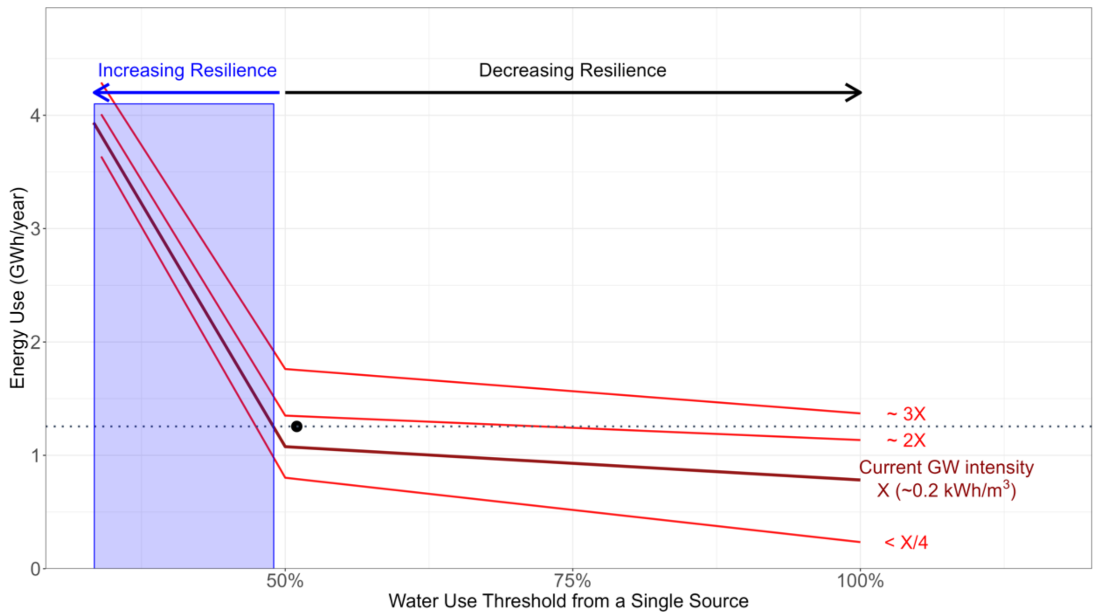

Figure 4.11. Sensitivity analysis changing water use threshold for each facility for different groundwater intensities

This study aimed to develop a method for optimizing embedded energy/GHG emissions associated with manufacturing water supply. To test the method, the authors applied it to the manufacturing water usage for Assumption Parish, LA. The results indicate that resilience in this county comes at the expense of energy use. A broader study that includes more counties might shed more light on the interdependencies between water usage, water source, energy consumption, and GHG emissions. In the future, investigators could develop criteria to determine when such analyses could be useful and institute similar frameworks for other geographies, such as states and regions. An aspirational goal would be to create an easy-to-use, interactive tool for policymakers to estimate potential energy/GHG savings at the county, state, and national levels.

4.4.2.2 Cost Benefits for Industrial Users and Auxiliary Benefits

Section 4.4.2.2 Summary

- This section performs an exploratory analysis to determine how much of U.S. manufacturing wastewater could be cost-effectively treated with curtailed electricity arising from increased renewables penetration.
- Ruth, Jadun, and Cole (2023) estimated the impact on the amount of curtailed electricity based on offering different payments to generators for curtailed electricity. The authors' supplemental analysis shows that a payment of $30/MWh (roughly half the cost of electricity of average industrial users) supplies enough curtailed electricity to meet water reuse treatment for U.S. manufacturing discharges.

There are potential opportunities to increase coordination of the water and electric systems. Past studies have examined opportunities for the water system to participate in the electric system through demand response (DR) programs and/or shifting treatment and pumping loads. Stoll, Buechler, and Hale (2017) identified flexible loads in Florida that could potentially participate in DR programs. Specific to the water industry, the study found potential for shifting loads of water heating, wastewater pumping, water distribution pumping, and agricultural pumping activities. Load shifting would often involve pre-heating water or pressurizing water pipes during times of low load (night) or high solar generation (middle of the day). The participation of both water and electric loads could result in a 1% reduction of energy system costs and reduce the number of times coal and natural gas peaking plants are started, resulting in reduced emissions. Even though the impacts were small, the study identified initial operations for various loads to participate in DR programs (Stoll, Buechler, and Hale 2017).

Specific to water and wastewater plants, Liu and Mauter (2020) identified DR opportunities across water utilities in the U.S. Their study identified opportunities for shifting pumping and treatment loads within a wastewater treatment plant and distribution system. The analysis found that DR opportunities varied across different regions and by time of year, with a maximum reduction of peak load from 610 MW to 140 MW in July for a single plant. However, the opportunity was minimal across the wastewater treatment sector, but this could change over time with the development of new technologies and the electrification of wastewater treatment processes (Liu and Mauter 2020).

As both of these recent studies found, there are currently limited opportunities for DR within wastewater treatment plants with current technologies and configurations. More flexible treatment technologies and higher penetrations of solar and wind will increase curtailed electricity during times of high renewable generation. These developments may present opportunities for load shifting of treatment times to take advantage of cheap, curtailed electricity. This section of the report combines an existing analysis that identified otherwise curtailed electricity (OCE) based on different electricity prices offered (Ruth, Jadun, and Cole 2023) with an estimate of water treatment needs for industrial wastewater sources to identify the opportunity space for shifting treatment loads. Flexible treatment operations could potentially reduce electricity prices, provide manufacturers with another revenue stream, and benefit the overall electric grid.

Ruth, Jadun, and Cole (2023) calculated the amount of curtailed electricity available in the U.S. electric system if different prices for curtailed electricity were offered to generation plants. Using the Regional Energy Deployment System (ReEDS),[33] different prices for curtailed electricity ranging from $0/megawatt-hour (MWh) to $30/MWh in increments of $5/MWh were offered to generating plants to identify the response of electric generators deployed. ReEDS calculates energy deployment over 134 power control areas (PCAs) and can identify responses to different installation costs, electricity prices, and demand scenarios for the different regions. As more wind and solar plants are installed, there will likely be an increased need to curtail electricity at certain times of the day. Currently, generators do not receive any compensation for this curtailed electricity. However, with a small economic incentive, there could be an increase of curtailed electricity from roughly 100–300 TWh/yr at $0/MWh to 3,500–4,200 TWh/yr at $30/MWh across the country, mainly from solar and wind generators. This increase of available curtailed energy will be designated OCE for the rest of this section.

The report authors calculated the amount of OCE by PCA for 2030 to represent the amount of curtailed electricity potential available for flexible industrial wastewater treatment. There are seasonal and regional trends for OCE. There is slightly more OCE in the spring and fall compared to the summer and winter, likely due to reductions in wind energy in the summer and solar energy in the winter, as well as moderate temperatures reducing heating and cooling load demand. Regionally, differences depend on resource availability, with more wind in the Midwest region leading to flatter OCE availability profiles and solar resources in the Southwest leading to more variation during the day when solar generation peaks.

To estimate the amount of electricity needed for industrial water treatment by balancing PCA, report authors obtained water discharge volumes from the EPA DMR for 2017. They then matched these discharge volumes to the ReEDS PCA areas to represent the amount of industrial water to treat in each individual region. Industrial point sources discharged roughly 14,400 BG of wastewater in 2017 as reported in the DMR. Report authors assumed that these water discharge values would remain constant over the analysis period to 2050 due to the lack of water discharge projections in the future. Given the wide range of constituents in wastewater discharge, a range of electricity intensities represents the low and high electricity values for currently available water reuse technologies. Report authors chose the treatment train to represent treatment for reuse to be coagulation, flocculation, clarification, ultra-filtration, reverse osmosis, and UV/oxidization, based on a past study from Yin et al. (2019). The range of water treatment electricity intensity was 0.85 kWh/m^3 (3220 kWh/MG) for on the low end and 1.88 kWh/m^3 (7116 kWh/MG) on the high end. Note that Yin et al. (2019) reported ranges for potable water reuse that may have an impact on total electricity intensity for other potential uses of water in industry. Coupling the amount of water discharged by balancing with the energy intensity of water treatment allowed for calculating the range of electricity needed by PCA to treat industrial wastewater. For industrial wastewater discharges in 2017, the report authors estimated 44 TWh for the low electricity intensity and 96 TWh for the high intensity. They then performed a geospatial analysis to examine the total energy needed for treatment by PCA and to calculate the OCE price needed to deploy enough OCE to match the electricity needed for

[33] https://www.nrel.gov/analysis/reeds/

treatment by balancing authority. Figure 4.12–Figure 4.15 display the results:

- Figure 4.12 represents the amount of OCE available by PCA for different OCE prices.
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- Figure 4.13 represents the amount of electricity needed by PCA to treat industrial wastewater for low and high intensities.
- Figure 4.14 represents the price of OCE needed to produce enough OCE to treat industrial wastewater by PCA.
- Figure 4.15 represents the percentage of PCA with enough OCE available to treat all the industrial water by OCE price.

This analysis shows that there is an initial matching of OCE available and electricity demand for water treatment in the U.S., and there is enough OCE available at $30/MWh to treat industrial wastewater in most PCAs. As of June 2020, the average price of electricity for industrial sources was $0.0717/kWh (EIA 2020). Even at the high OCE price ($0.03/kWh), industrial plants would still realize cost savings in utilizing OCE for water treatment ($0.0417/kWh reduction). These cost savings would need to be balanced by numerous costs to enable flexibility. First, the manufacturer might need to update or install water treatment technologies to enable flexible water treatment. Second, because water treatment would be delayed, tanks would need to be installed on-site to store water for treatment. For example, a 5,000-gallon fiberglass tank would cost roughly $17,400 to install, based on cost models from the EPA (2023). A manufacturer would need to offset around 410,000 kWh to pay for the tank alone, which might not be cost-effective. Finally, operators would need training to operate these flexible systems, and it would take time to change operations. At current electricity prices and installation costs, there are likely higher payback opportunities within a plant, but this might change over time. As water resources become scarce, there is some potential to utilize the roughly 14,000 BG of treated wastewater for reuse within the plant, and this could be an alternative water source for plants in drought areas.

Along with cost considerations, there are other operational and institutional concerns for implementing these flexible systems. More research regarding flexible and variable treatment trains (reuse treatment technology, storage, water reuse infrastructure, etc.) is needed to ensure there is not system degradation or concerns with meeting environmental permits. Plant managers might consider investments in water systems and upgrades a lower priority because water costs often comprise around 1% of total expenditures. There will also be competition concerns with the use of OCE if other electricity users (HVAC, demand response aggregators, hydrogen production, etc.) adopt this practice. Widespread adoption could reduce the effectiveness of installation if the supply of OCE is scarce. This analysis shows that there are opportunities for coordination of the electricity sector and wastewater treatment resources, but more R&D for treatment technologies and quantification of the economics of these systems is needed to calculate the economic opportunity.

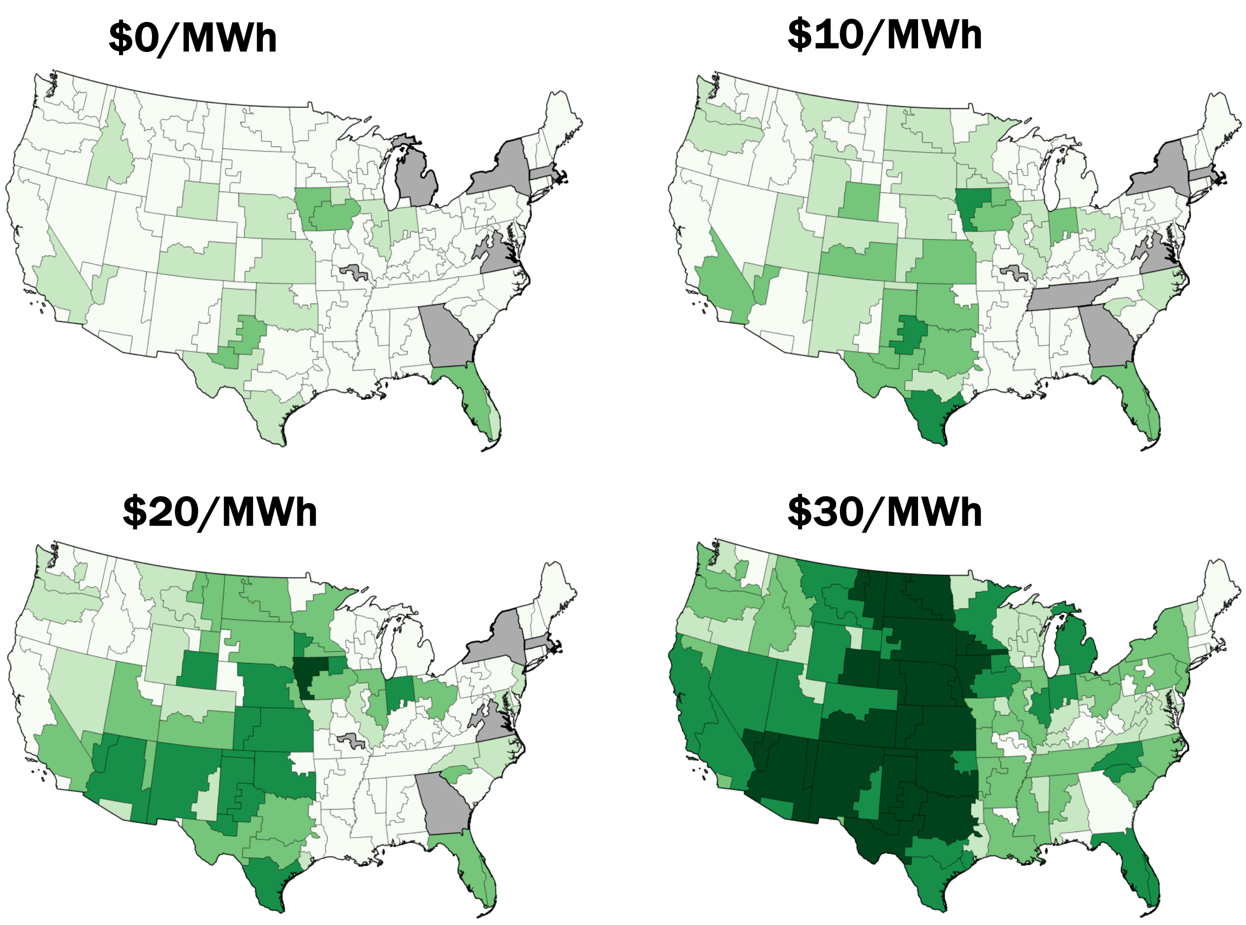

Figure 4.12. Amount of OCE available by PCA and OCE price
Gray indicates no OCE was available for that given price

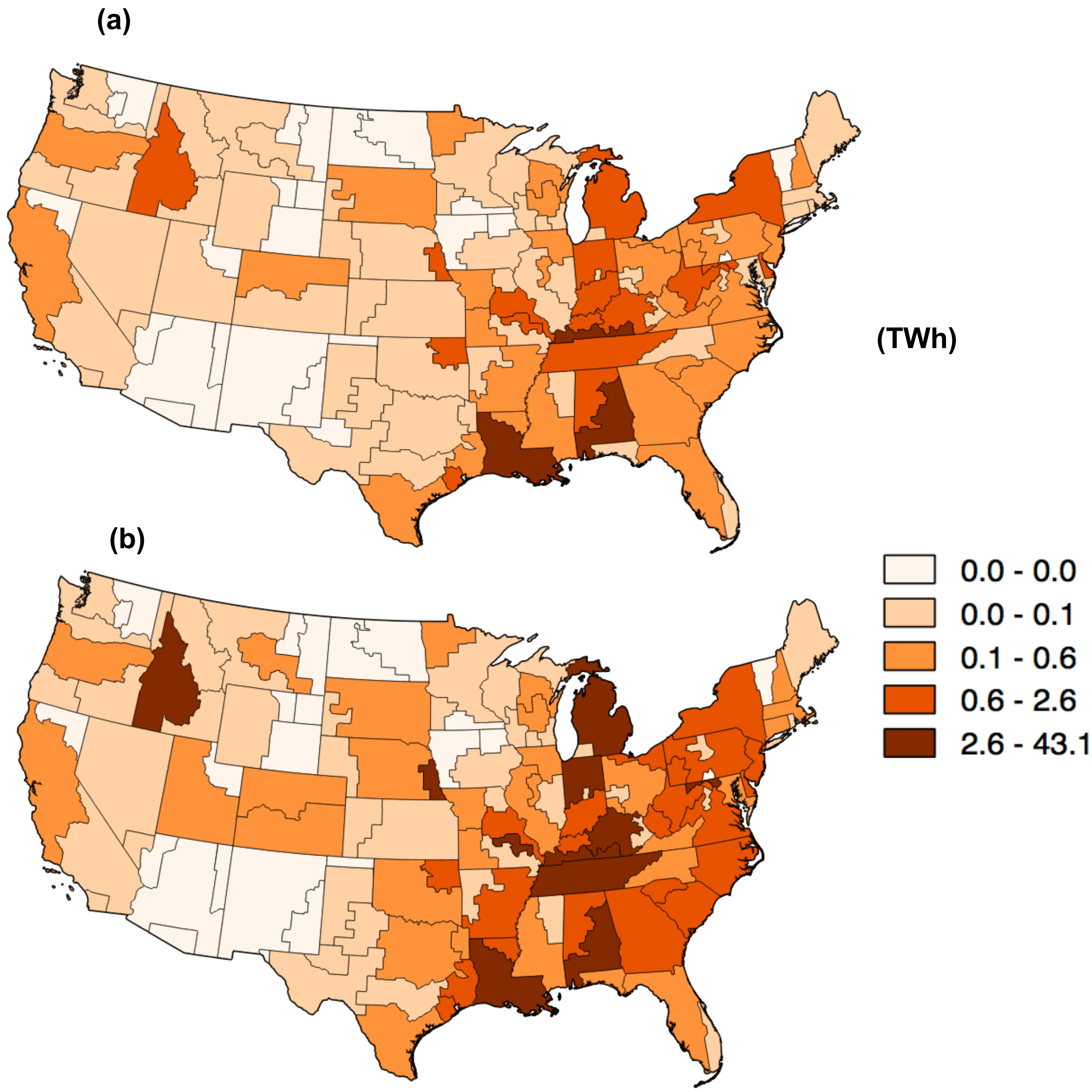

Figure 4.13. Electricity needed to treat industrial waste by PCA at low intensity (a) and high intensity (b)

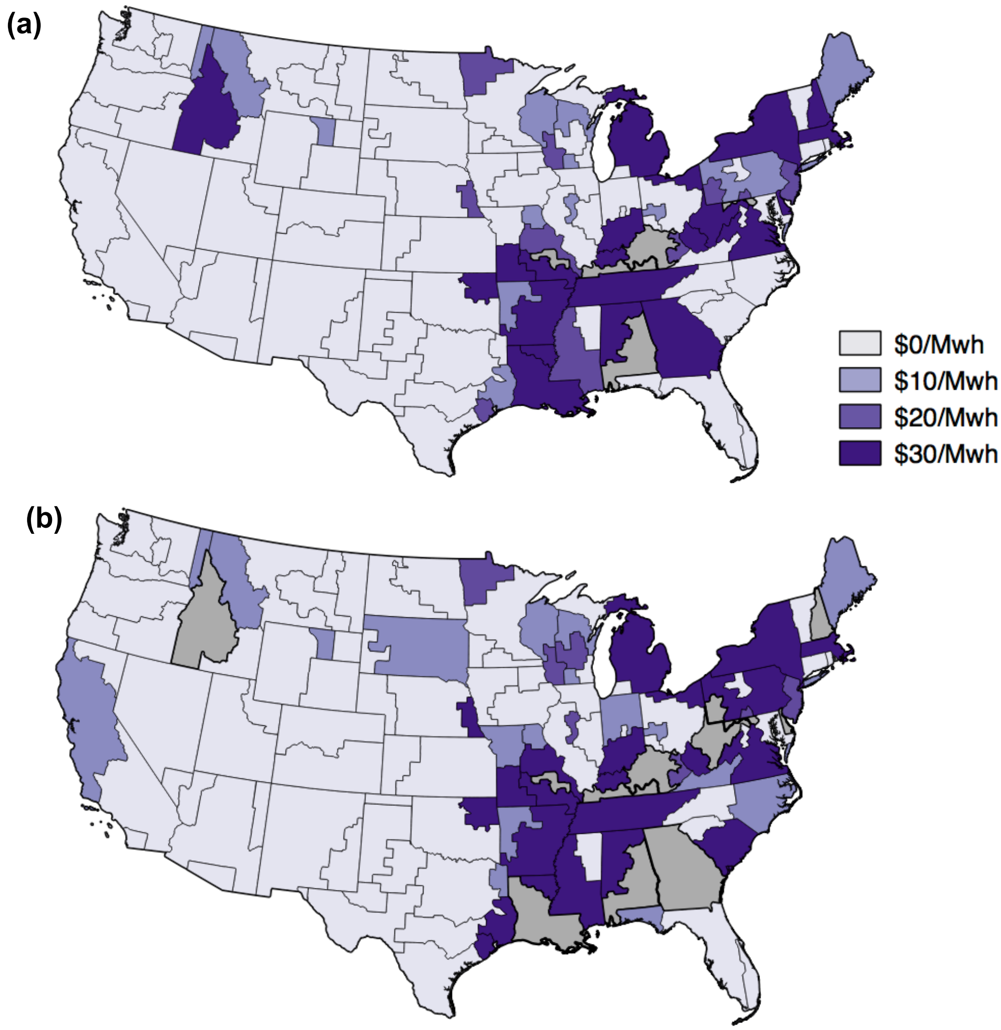

Figure 4.14. OCE price needed to produce enough OCE to treat 100% of industrial wastewater by PCA at low intensity (a) and high intensity (b)

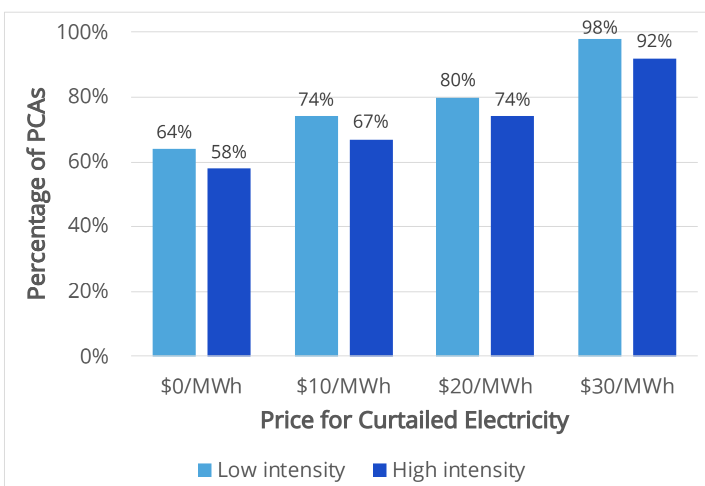

Figure 4.15. Share of PCAs with enough OCE to treat 100% of industrial wastewater at low and high intensity

5. Conclusions

Significant risks to manufacturing water supplies are no longer theoretical. Nor are the negative environmental and societal water-related impacts of manufacturing operations. As climate change accelerates and industrial development proceeds apace, many increasingly acknowledge the reality of our collective, pressing need for decarbonization—but far fewer understand the many risks to sustainable and sufficient water supplies for manufacturing operations and their watersheds laid out in Section 1 of this report. Research, development, demonstration, and deployment (RDD&D) of new technologies and approaches are urgently needed to achieve resilience of this essential resource in the manufacturing sector.

Good information is critical to mitigate risk. The paucity of industrial water data is thus problematic, with no consistent nationally or regionally representative datasets collected or publicly available. A better understanding of manufacturing water use would foster systemic improvements at the nexus of risk, water, and energy in the manufacturing sector. Section 2 contextualizes available water use estimates required for comprehensive risk analyses, illustrating that more accurate and representative data on water intake, consumption, and discharge are required to achieve actionable technology assessments, as well as assist manufacturers in conserving water to advance resilience.

Another issue impeding progress toward resilience is that water is ubiquitously and significantly undervalued in manufacturing. Section 3 distinguishes between water price, cost, and value, asserting that the true value of water encompasses the price paid, its "true cost" (e.g., direct user ancillary costs related to chemicals, energy, permits, and maintenance), other internal costs (e.g. costs of alternative water supply and retooling), and indirect/opportunity costs (e.g., environmental and economic externalities). It summarizes various facility, sectoral, and regional water valuation metrics that can help identify technology requirements and effects and presents case studies of manufacturers making efforts to appropriately value water. Manufacturers that are aware of the full value of water are better able to evaluate technology opportunities and manage water-related risks while improving their reputation and operational resilience.

Section 4 highlights RDD&D opportunities for technology innovation by presenting exemplars of advanced analyses that can be further developed to identify such opportunities and resilience strategies. At the plant level, the Plant Water Profiler (PWP) tool integrates water valuation concepts in identifying the true cost of water-using subsystems and processes. In addition, water-less or water-lean technologies have the potential to reduce on-site water use and achieve additional benefits, but their effects must be comprehensively considered over their life cycle. On-site water reuse also promises to increase resilience if not achieved at the expense of unacceptable energy use and associated GHG emissions. On a larger scale, tradeoffs between water supply resilience and embedded emissions can be evaluated via a framework applied in this section. Finally, flexible wastewater treatment scheduling could achieve valuable load shifting and/or demand response in the electricity sector, but accurately assessing the scale of such an opportunity first needs additional research and development.

Ultimately, this report emphasizes that water stress for manufacturers is exacerbated by our rapidly changing climate, increased competition for limited water supplies, and water undervaluation. The dearth of data describing who, when, where, and how water is used for manufacturing—as well as water quantity, quality, and source—inhibits informed water management and decision-making. Additionally, though not addressed in this report but critical to consider, the environmental justice implications of manufacturing water withdrawals may become more pronounced as water allotments—either officially by a water authority or as perceived by a community—take shape in response to growing water scarcity. Future research, analysis, and action should be framed through the lens of these two intertwined issues. However, without additional data, research, and technology development, water stress and associated risks are likely to result in cascading and increasingly severe consequences for the manufacturing sector and stakeholders of all kinds in surrounding watersheds.

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Appendix A. Multi-Variable Regression Method References

This Appendix provides the data sources used for the multi-variable regression using Statistics Canada data to predict manufacturing water intake across Canadian manufacturing industries (see Section 2.2.4.2).

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Appendix B. Price Elasticity of Water Demand

Table B.1 provides the references and data used for Figure 3.3.

Table B.1 Price elasticity of water demand across countries and manufacturing subsectors

NAICS code	Subsector	Price elasticity of water demand							
		Vásquez-Lavín et al. (2020)	Köseoğlu (2018)	Nahman & De Lange (2012)	Kumar (2006)	Rojas (2005)	Dupont & Renzetti (2000)	Wang & Lall (1999)	Babin, Willis & Allen (1982)
		Chile	U.K. (Scotland)	South Africa	India	Mexico	Canada	China	United States
31-33	Manufacturing sector	-1.23	-0.8	-3	-0.9	-0.29	-0.8	-1.03	-0.56
311	Food manufacturing	-1.18	-0.8	-0.78	-0.92	-	-	-1.04	0.14
312	Beverage & tobacco product manufacturing	-1.16	-0.8	1.1	-0.91	-	-	-1.04	-
313	Textile mills	-1.23	-1.4	-2.08	-	-	-	-1.1	-
314	Textile product mills	-	-1.4	-2.08	-	-	-	-	-
315	Apparel manufacturing	-1.24	-1.4	-	-	-	-	-	-
316	Leather & allied product manufacturing	-2.73	-	-	-0.94	-	-	-1.2	-
321	Wood product manufacturing	-1.12	-	-6.81	-	-	-		-
322	Paper manufacturing	-1.36	-1.4	-6.81	-	-	-	-0.88	-0.66
323	Printing & related support activities	-	-	-	-	-	-	-	-
324	Petroleum & coal products manufacturing	-	-1.8	-5.19	-	-	-	-0.99	-

325	Chemical manufacturing	-1.22	-0.9	-5.69	-0.92 chemicals -0.30 drugs	-	-	-0.96	-
326	Plastics & rubber products manufacturing	-1.26	-	-	-	-	-	-	-
327	Nonmetallic mineral product manufacturing	-1.27	-	-	-	-	-	-	-
331	Primary metal manufacturing	-1.28	-	-5.08	-	-	-	-0.85	-
332	Fabricated metal product manufacturing	-	-	-	-	-	-		-0.41
333	Machinery manufacturing	-1.5	-	-	-	-	-	-1.03	0.14
334	Computer & electronic product manufacturing	-	-	-3.05	-	-	-	-1.14	0.54
335	Electrical equipment, appliance, & component manufacturing	-1.21	-1.8	-3.05	-	-	-	-	0.54
336	Transportation equipment manufacturing	-1.15	-	-3.13	-	-	-	-1.16	-
337	Furniture & related product manufacturing	-1.21	-	-	-	-	-		
339	Miscellaneous manufacturing	-	-	-	-0.87	-	-	-	-