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Life Cycle Assessment of Upgrade Options to Improve Nutrient Removal for the City of Santa Fe, NM, Paseo Real Wastewater Treatment Plant

Prepared for:

U.S. Environmental Protection Agency
Standards and Health Protection Division
Office of Water, Office of Science and Technology
1200 Pennsylvania Avenue NW (4305T)
Washington, DC 20460

Prepared by:
Eastern Research Group, Inc.
110 Hartwell Ave
Lexington, MA 02421

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EXECUTIVE SUMMARY

Nutrient pollution of waterbodies across the United States is one of the most pervasive environmental issues facing the country today.[1] In partnership with states, tribes, and other federal agencies, the U.S. Environmental Protection Agency (EPA) has led efforts to address nutrient pollution by providing scientific and technical assistance for implementing nutrient-based policies and regulations, including numeric nutrient water quality criteria, total maximum daily loads, and effluent limits for point source dischargers.

Recently, wastewater treatment plant (WWTP) operators and stakeholders have expressed concern over the potential for significant environmental and health implications associated with treatment technologies required to achieve more stringent effluent concentrations for nutrients (i.e., nitrogen and phosphorus) (Falk et al., 2013; U.S. EPA, 2022a). For example, greater use of materials and energy results in potentially greater emissions of toxic chemicals and greenhouse gases. Studies are beginning to suggest there could be a point of diminishing returns where the economic and environmental consequences of advanced treatment begin to outweigh the benefits of greater nutrient removal (Falk et al., 2013; Foley et al., 2010).

The Paseo Real WWTP (PR WWTP), which serves the City of Santa Fe, New Mexico, is faced with the challenge of balancing the need for improved nutrient removal while limiting additional environmental impacts. The city recently commissioned a Nutrient Loading and Removal Optimization Study, which developed and evaluated several options for process optimization and upgrading to meet more stringent effluent nutrient limitations. That study identified reverse osmosis (RO) as the technology that would result in the lowest effluent nutrient concentrations. However, the city has expressed the same concerns as others (Falk et al., 2013; Foley et al., 2010) related to the cost, practicality, and coincident environmental impacts associated with an RO system.

The objective of this study is to conduct a life cycle assessment (LCA) of the upgrade options available to the PR WWTP. LCA is a widely accepted, systematic technique to assess and quantify the holistic environmental aspects and potential impacts associated with individual products, processes, or services. In 2021, EPA completed an LCA of generalized WWTP configurations (U.S. EPA, 2021a) that demonstrated the potential for considerable increase in environmental impacts associated with technologies designed to achieve the highest level of nutrient removal. This study uses a similar methodology applied to an actual case study system. The treatment configurations evaluated by this study were designed specifically for the PR WWTP (Carollo Engineers, 2018) and are described in Table ES-1.

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[1] United States Environmental Protection Agency. 2022 EPA Nutrient Reduction Memorandum. *Accelerating Nutrient Pollution Reductions in the Nation's Water* (April 2022).

Table ES-1. Summary of Treatment Scenarios Evaluated for this Study.

Proposed Scenarios	Target Effluent Conc. (mg/L)		Description
	Total Nitrogen	Total Phosphorus	
Baseline	5	1	The Baseline Scenario is the anticipated state of the facility following implementation of all currently planned facility upgrades, including upgraded aeration system, a combined heat and power system, and partial effluent diversion to the Rio Grande.
Scenario 1 – Sidestream Filtration	4.5	0.7	Scenario 1 is the Baseline configuration with the addition of sidestream filtration, which includes treatment of the high nutrient concentration filtrate that is generated from sludge dewatering processes.
Scenario 2 – Tertiary Filtration	3	0.05	Scenario 2 is the Baseline configuration with the addition of tertiary deep bed media filters and new chemical feed facilities for enhanced nutrient removal.
Scenario 3 – Reverse Osmosis	2	0.05	Scenario 3 is the Baseline configuration with the addition of a microfiltration/reverse osmosis system downstream of the secondary clarifiers.
Scenario 4 – Zero Discharge	5	1	Scenario 4 assumes the same facility configurations as the Baseline Scenario, with no discharge to the Santa Fe River. All current effluent discharges to the Santa Fe River would instead be diverted to the Rio Grande using a larger pipeline than currently planned under the Baseline Scenario. The city would continue serving its non-potable reuse customers' needs.

This study uses 12 standard LCA metrics that describe potential environmental, energy and climate, water, and toxicity impacts, as well as cost estimates for each configuration. Life cycle inventories (LCIs[2]) of each configuration were developed in collaboration with the study workgroup, which includes staff from EPA, the New Mexico Environment Department, the City of Santa Fe (including staff from the PR WWTP), Carollo Engineers, and Eastern Research Group, Inc. (ERG). Where possible, uncertainty ranges in LCI inputs were defined and used in subsequent Monte Carlo simulations to describe ranges of uncertainty in study results. The study's system boundary includes all relevant details of the wastewater treatment processes, environmental releases from each process, and the supply chains associated with inputs to each process. Study results are provided on the basis of a standard volume of water treated by each configuration to different effluent nutrient concentration targets.

LCA results across all scenarios and metrics are provided in Figure ES-1. Results for each metric have been standardized to a common scale of -1 to 1 by dividing results by the maximum and minimum values across all Scenarios. Results show that Scenario 3 (Reverse Osmosis) has the lowest eutrophication potential impacts but the highest impacts across all other metrics. Additionally, water scarcity impacts, which consider life cycle water use as well as local water scarcity, suggest that Reverse Osmosis would result in much greater impacts than all other scenarios due to the brine disposal process, which renders water associated with the injected

[2]LCIs provide a list of all input and output flows to the system under investigation. Inputs may include raw materials, energy or water, and outputs may include emissions to water, land or air.

brine unavailable for other purposes. Monte Carlo uncertainty results indicate that, within the range of uncertainty of the treatment performance assumptions, Scenario 2 (Tertiary Filters) eutrophication potential impacts are comparable to those of Reverse Osmosis. Figure ES-1 shows that Tertiary Filters would result in lower potential impacts across all other metrics.

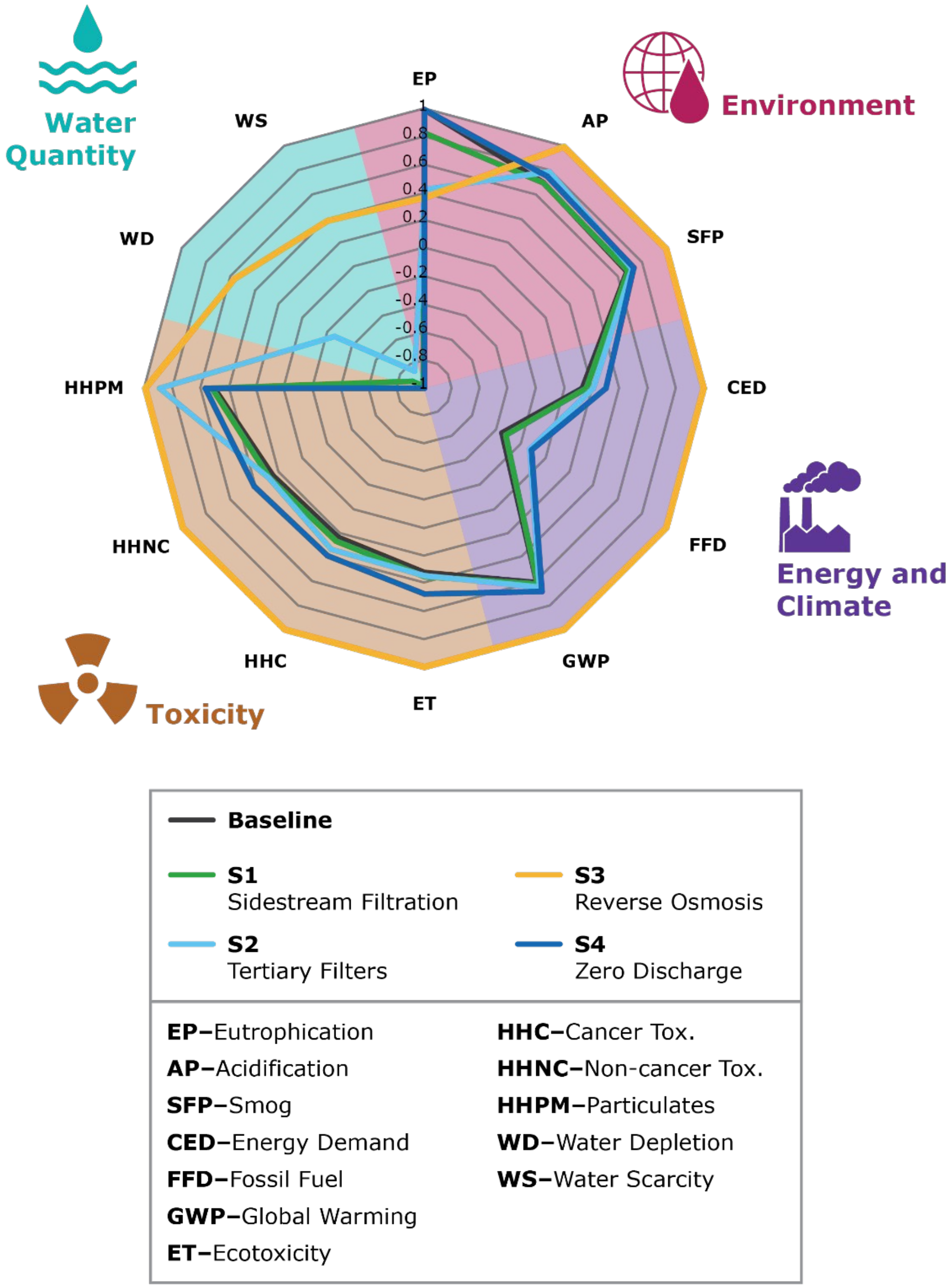

Figure ES-1. Standardized Results from Each Study Treatment. A value of 1 (i.e., toward the outer edge of the plot_ reflect the greatest environmental harm, while a value of -1 (i.e., toward the center of the plot) reflects the least environmental harm.

LCA results also show that Scenario 1 (Sidestream Filtration) can achieve about a 17% improvement in eutrophication potential relative to the Baseline Scenario, while potential impacts across all other metrics result in increases ranging from 1% to 6% relative to the Baseline Scenario. This suggests that, in terms of impact per unit of nutrient removed, Sidestream Filtration may be more efficient than the other evaluated technology options, which is also supported by a nutrient removal standardization analysis performed in the study (Section 3.5.3). Despite resulting in greater impacts across some of the other metrics, Tertiary Filters and Reverse Osmosis result in eutrophication potential reductions of approximately 57% and 63%, respectively, relative to the Baseline Scenario.

Scenario 4 (Zero Discharge), which accounts for the additional energy required to divert the majority of PR WWTP effluent to the Rio Grande, results in similar impacts to the Baseline Scenario for eutrophication potential (this study assumes eutrophication impacts of effluent discharge do not depend on discharge location), water depletion, and water scarcity. The Zero Discharge scenario results in slightly higher impacts than the Baseline Scenario for all other metrics, owing to the minor increases in material and energy requirements of full effluent diversion compared to partial effluent diversion.

Results normalization, standardization, and sensitivity analyses were performed to contextualize the study results. Normalization is an optional step in life cycle impact assessment that indicates the significance of impact category results by calculating their contribution to total category impact on a regional or per capita basis. Normalized results (Section 3.5.1) show that as a share of average U.S. per capita impacts, eutrophication potential impacts are larger than contributions from all other impact categories, ranging from 2% to 5% for each scenario. The water depletion category also has relatively high normalized impacts, ranging from -2% for the Baseline Scenario and Scenario 4 (due to water reuse) to 1.2% for Scenario 3. Contributions from other impact categories range from 0.01% to 0.42% of average per capita burdens across all scenarios.

Standardizing impacts to units of nutrients removed (a proxy for nutrient removal efficiency—see Section 3.5.3) showed no changes to the relative rankings of alternatives under baseline study results but showed progressively decreasing efficiency with increasing levels of treatment, with the largest decreases mostly occurring between Tertiary Filters and Reverse Osmosis.

Sensitivity analyses (Section 4) examine the influence of key parameters, eutrophication potential characterization factors, global warming potential characterization factors, electricity grid mix, and sludge management on the environmental performance of treatment scenarios. Compared to baseline results, sensitivity results show that relative rankings between scenarios generally remain unchanged across the range of sensitivity assumptions; however, the magnitude of difference in impacts between scenarios is affected. For example, the eutrophication potential sensitivity analysis accounts for bioavailability of organic nitrogen, which is the dominant effluent nutrient contributor to eutrophication potential impacts for the more advanced nutrient removal scenarios (Tertiary Filtration and Reverse Osmosis). Under conditions where organic nitrogen may be less bioavailable, eutrophication potential impacts of all scenarios are reduced, and the relative difference between Tertiary Filters and Reverse Osmosis is lessened. Impacts of Tertiary Filters were found to be sensitive to alum dosing. Using more alum than anticipated could result in water depletion impacts for Tertiary Filters comparable to Reverse Osmosis. The electricity grid sensitivity analysis shows that if a greater fraction of solar energy were used, impacts across all scenarios would be reduced, though reductions for eutrophication potential and water depletion would be minor. Impacts for the particularly energy-intensive Reverse Osmosis scenario would, for some metrics (e.g., cancer and noncancer toxicity, smog formation, fossil fuel depletion), be more comparable to, and sometimes less than, other treatment configurations.

Results of this study, summarized in Table ES-3, reinforce the findings of previous research (Falk et al., 2013; U.S. EPA, 2022a), showing that increasingly advanced levels of nutrient removal lead to improved water quality while producing greater environmental impacts in other categories and at higher costs. Sidestream Filtration (Scenario 1) would result in small improvements to nutrient removal with correspondingly small increases in potential environmental impacts. Reverse Osmosis (Scenario 3) offers the greatest potential for improved nutrient removal but does so at the expense of potentially greater environmental impacts compared to all other scenarios being considered in this analysis. Zero Discharge (Scenario 4) would result in comparable nutrient emissions to the Baseline Scenario and only small increases in environmental impacts associated with diverting effluent to the Rio Grande.

Table ES-2. Summary of Study Results.

LCA Results	S1 - Sidestream Filtration	S2 - Tertiary Filters	S3 - Reverse Osmosis	S4 - Zero Discharge
Impact	Small increases in potential environmental impacts	Small to moderate increases in potential environmental impacts	Except for eutrophication potential, potential environmental impacts generally much greater than other scenarios considered	Small increases in impacts associated with full effluent diversion
Benefit	Small improvement to nutrient removal	Large improvement to nutrient removal	Largest improvement to nutrient removal	Eutrophication potential impacts diverted from Santa Fe River to Rio Grande

NOTICE

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The facility operating information and related analyses in this document are based on data received from the facility featured in this document. While EPA has reviewed and evaluated these data, EPA does not assume responsibility for the accuracy of the data used in the analyses. Neither the data used in this report nor the technology evaluations provided here nor the conclusions or results reported in this document substitute for site-specific analysis needed when considering the use of these technologies at other facilities.

Technology performance and variability in effluent concentrations, particularly for nutrient removal, is affected by site-specific factors such as process design, wet weather flow, variability in influent flow and concentrations, process control capabilities, presence of biological inhibitors or toxics, presence of equalization tanks, sidestreams, and many other factors. In addition, a plant's actual flow and nutrient loading relative to the design capacity could be a significant factor that impacts performance. As such, the information in this report can be viewed as a guide based on the investigated plant's actual operation over 36 months but should not be used to translate performance or variability to other plants without careful consideration of the plant's site-specific conditions.

This document is intended to be solely informational and does not impose legally binding requirements on EPA or other U.S. federal agencies, states, local, or tribal governments, or members of the public.

ACRONYMS AND ABBREVIATIONS

AP	Acidification potential
AS	Activated sludge
AWARE	Available WAter REmaining method
AZNM	Arizona/New Mexico eGRID subregion
BFP	Belt filter press
BOD	Biochemical oxygen demand
CBOD	Carbonaceous biochemical oxygen demand
CED	Cumulative energy demand
CHP	Combined heat and power
CO	Carbon monoxide
COD	Chemical oxygen demand
DAF	Dissolved air flotation
DAP	Diammonium phosphate
DBP	Disinfection byproduct
DQI	Data quality indicator
EF	Emission factor
eGRID	Emissions & Generation Resource Integrated Database
eLCI	Electricity LCI
EON	Effluent organic nitrogen
EP	Eutrophication potential
EPA	U.S. Environmental Protection Agency
ERG	Eastern Research Group, Inc.
ET	Ecotoxicity
FP	Formation potential
GHG	Greenhouse gas
GT	Gravity thickener
GWP	Global warming potential
H_2S	Hydrogen sulfide
HAB	Harmful algal blooms
HH	Human health
HHC	Human health cancer potential
HHNC	Human health noncancer potential
HHPM	Human health particulate matter formation potential
HHV	High heating value
ICE	Internal combustion engine
ISO	International Organization for Standardization
LCA	Life cycle assessment
LCCA	Life cycle cost analysis
LCI	Life cycle inventory
LCIA	Life cycle impact assessment
m^3	cubic meter
MBR	Membrane bioreactor
MCF	Methane conversion factor
MF	Microfilter
MGD	Million gallons per day
N	Nitrogen
NM	New Mexico
NMED	New Mexico Environment Department

NNC	Numeric nutrient criteria
NOM	Natural organic matter
NO_X	Nitrogen oxides
ORD	U.S. EPA Office of Research and Development
P	Phosphorus
PM	Particulate matter
PPCP	Pharmaceuticals and personal care products
PR	Paseo Real
QAPP	Quality Assurance Project Plan
RO	Reverse osmosis
SFP	Smog formation potential
SFR	Santa Fe River
TKN	Total Kjeldahl nitrogen
TN	Total nitrogen (Total Kjeldahl Nitrogen + Nitrate/Nitrite)
TP	Total phosphorus
TRACI	Tool for the Reduction and Assessment of Chemical and Environmental Impacts
UF	Ultrafiltration
UIC	Underground injection control
UNFCCC	United Nations Framework Convention on Climate Change
US LCI	United States Life Cycle Inventory Database
UV	Ultraviolet
VOCs	Volatile organic compounds
WD	Water depletion
WECC	Western Electricity Coordinating Council
WQS	Water quality standard
WS	Water scarcity
WWT	Wastewater treatment
WWTP	Wastewater treatment plant

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1. INTRODUCTION AND OBJECTIVE

Nutrient pollution of waterbodies across the United States is one of the most pervasive environmental issues facing the country today. Whether in lakes or reservoirs, rivers or streams, estuaries or marine coastal waters, the human health, environmental, and economic impacts from excessive amounts of nitrogen (N) and phosphorus (P) continue to rise every year. Communities struggle with nutrient-fueled harmful algal blooms (HABs), which produce toxins that can sicken people and pets, contaminate food and drinking water sources, destroy aquatic life, and disrupt the balance of natural ecosystems. HABs can raise the cost of drinking water treatment, depress property values, close beaches and fishing areas, and negatively affect the health and livelihood of many Americans (U.S. EPA, 2015). Global climate change is only expected to exacerbate eutrophication even as federal, state, and local governments struggle to address the sources of nutrient pollution (USGCRP, 2016).

In partnership with states, tribes, and other federal agencies, the U.S. Environmental Protection Agency (EPA) has led the effort to address nutrient pollution by helping states prioritize waters; providing scientific and technical assistance with developing water quality standards for total nitrogen (TN) and total phosphorus (TP); and helping to guide implementation of nutrient criteria including total maximum daily loads for impaired waters and water quality-based effluent limits for point source dischargers. Given the urgency of the problem, EPA's Office of Water plans to accelerate progress in controlling nutrient pollution in the nation's waters by scaling up existing, foundational approaches and more broadly deploying new data assessments, tools, financing approaches, and implementation strategies (U.S. EPA, 2022b). Additionally, EPA plans to integrate the objectives of both the Safe Drinking Water Act and Clean Water Act in a One Water approach to find durable solutions to the challenges and costs associated with reducing nutrient pollution. At the same time, EPA foresees incorporating promising innovations, creative partnerships, and unprecedented opportunities to invest in clean and safe water in the Bipartisan Infrastructure Law to accelerate progress in reducing nutrient pollution.[3]

EPA has assisted states in translating their narrative criteria to protect waters from eutrophication.[4] In New Mexico, for example, the state's water quality standards (WQS) regulations[5] include a narrative criterion to protect aquatic life from nutrient conditions that contribute to production of undesirable or nuisance aquatic life. The criterion states, "Plant nutrients from other than natural causes shall not be present in concentrations that will produce undesirable aquatic life or result in a dominance of nuisance species in surface waters of the state" (20.6.4.13.E New Mexico Administrative Code). In other words, non-zero nutrient concentrations that will not produce undesirable effects are acceptable. The state translates this narrative criterion using numeric threshold values in its Comprehensive Assessment and Listing

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[3] For more information, see the 2022 EPA Nutrient Reduction Memorandum website.

[4] "Eutrophication is defined as an increase in nutrient input to surface waters to the extent of over enrichment, with a corresponding increase in primary productivity and related negative effects" (Serediak et al., 2014).

[5] Codified at 20.6.4 NMAC.

Methodology (CALM),[6] which are based on reference conditions and applied to specific site classes in perennial, wadable streams. These numeric thresholds then become the basis for reasonable potential analyses and the development of water quality-based effluent limits in permits for point source dischargers. In most cases, this means potentially more stringent effluent limits for NM dischargers with the implementation of numeric thresholds requiring additional treatment to meet new limits.

Recently, operators and other stakeholders have expressed concern that there may be significant environmental and health implications when facilities move towards treatment technologies that remove more TN and TP to attain very low nutrient targets (e.g., Falk et al., 2013; U.S. EPA, 2022a). For example, potential impacts other than eutrophication are associated with greater use of chemicals, disposal of biosolids and brine (e.g., from reverse osmosis [RO]), increased energy demands, and greater release of greenhouse gases (GHGs). Studies in other countries also suggest a point of diminishing returns where the economic and environmental consequences begin to outweigh the benefits (e.g., Foley et al. 2010; Falk et al. 2013).

1.1 Case Study System

The Paseo Real (PR) wastewater treatment plant (WWTP), which is owned and operated by the City of Santa Fe, New Mexico, is one such facility challenged with balancing the need for improved nutrient removal while limiting additional environmental impacts. The PR WWTP discharges its effluent into the Santa Fe River, which is listed as "impaired" for nutrients and *Escherichia coli* (*E. coli*) bacteria. During certain parts of the year, flow in the Santa Fe River is almost entirely composed of discharge from the PR WWTP, which means the river's nutrient dynamics are highly sensitive to effluent concentrations at the PR WWTP. The New Mexico Environment Department (NMED) has developed numeric TN and TP thresholds to translate its narrative nutrient criteria, as shown in Table 1-1.[7, 8] The PR WWTP discharges to the Cienega Creek to Santa Fe WWTP portion of the Santa Fe River, which is characterized as site class TN Moderate and TP Flat-Moderate.

Table 1-1. Total Nitrogen (TN) and Total Phosphorus (TP) Causal Thresholds by Site Class.

Parameter and Site Class	Site Median Threshold (90th quantile) (mg/L)
TN Flat	0.69
TN Moderate	*0.42*
TN Steep	0.30
TP High-Volcanic	0.105
TP Flat-Moderate	*0.061*
TP Steep	0.030

Note: Thresholds that apply to Paseo Real WWTP are italicized.

[6] 2021 CALM. https://www.env.nm.gov/surface-water-quality/calm/

[7] Table 3, P.8 of Appendix C of NMED's 2021 CALM https://www.env.nm.gov/surface-water-quality/calm/.

[8] New Mexico and EPA apply the thresholds for permitting purposes as 30-day average values.

Although these thresholds are not WWTP effluent criteria, surface waters, and particularly those that are effluent-dominated, will generally not meet these thresholds if effluent nutrient concentrations are much higher. Moreover, these thresholds are lower than most facilities in New Mexico can currently achieve end-of-pipe, including the PR WWTP. This has led the City of Santa Fe and the State of New Mexico to evaluate operational and technological options for improving removal of nitrogen and phosphorus from the PR WWTP's effluent.

In 2018, the city completed a Nutrient Loading and Removal Optimization Study to examine the facility's options for process optimization and upgrading to meet one of several effluent "tiers"[9] for N and P removal (Carollo Engineers, 2018). The study identified several options to reduce effluent nutrient discharges. The identified options include optimization of the existing biological process and treatment of the filtrate return flow (Tier 1); installation of a membrane bioreactor (MBR) with chemical addition (Tier 2); installation of tertiary treatment with chemical addition (Tier 3); and installation of RO (Tier 4), which the study estimated could achieve the lowest effluent concentrations of all the options investigated. All proposed options would reduce nutrient releases relative to the 2018 status quo but would vary in their cost and ability to achieve the numeric nutrient thresholds for the Santa Fe River. Capital cost estimates provided in the Nutrient Loading and Removal Optimization Study ranged from $8.6 million for Tier 1 to $87 million for Tier 4.

While RO comes closest to achieving New Mexico's numeric nutrient thresholds, the city has expressed the same concerns as others (Falk et al., 2013; Foley et al., 2010) related to the cost, practicality, and cross-media environmental impacts[10] of an RO system.

The objective of this study is to conduct a life cycle assessment (LCA) on the PR WWTP in order to ascertain and quantify the potential environmental harms and benefits of various options for improving the removal of nutrients. LCA is a widely accepted, standardized, systematic technique to assess the holistic environmental aspects and potential impacts associated with individual products, processes, or services that can be applied to these kinds of issues. Often referred to as a "cradle-to-grave" analysis, LCAs reveal the presence of environmental trade-offs between "comparable" options, which indicates that no single option is typically capable of providing the best potential environmental performance across diverse impact categories. In 2021, EPA completed an LCA using generalized WWTP configurations titled, *Life Cycle and Cost Assessments of Nutrient Removal Technologies in Wastewater Treatment Plants* (U.S. EPA, 2021a). That study demonstrated the potential for a considerable increase in cross-media environmental impacts (e.g., energy demand, climate change potential) for technologies and treatment configurations designed to achieve the highest levels of nutrient removal. Building upon this earlier work, this current LCA study will provide data that can be useful to local, state, and federal decision-makers and other stakeholders make informed choices based on environmental considerations. These choices could potentially include informing treatment technology selection, balancing nutrient-water-energy nexus, future development of

[9] Note: "tiers," as used throughout this document, refers specifically to the treatment levels developed in Carollo Engineers 2018. This is not related to the term "tiers" as used in the context of antidegradation in water quality standards.

[10] "Cross-media" refers to the broad scope of LCA studies, considering the whole environment and not a single media (e.g., air, water, soil) or impact category.

revised water quality standards such as discharger-specific nutrient "temporary standards,"[11] revisions to the designated use, or revisions to site-specific criteria[12] for discharge into the Santa Fe River by the PR WWTP. This report only focuses on the technical analysis (i.e., the life cycle assessment itself) and does not address the policy implications of the results or future regulatory processes.

1.2 Paseo Real WWTP Background

The PR WWTP has been in operation since 1963, discharging treated effluent to the Santa Fe River. Its current design capacity is 13 million gallons per day (MGD) average maximum month flow or 12 MGD average day annual flow, with an average annual flow of 4.85 MGD. It serves approximately 85,000 residential customers, in addition to an unknown quantity of tourists and visitors (Carollo Engineers, 2018). In 2020, in an effort to update outdated equipment and improve their level of treatment, the facility began to implement a series of relatively low-cost upgrades including the installation of an upgraded aeration system with more energy-efficient blowers to allow for better control of dissolved oxygen levels. At the same time, the City of Santa Fe was in the process of installing a combined heat and power system to expand energy recovery from the biogas produced in the anaerobic digesters. The facility is also reviewing other options that provide a trade-off between nutrient removal and factors such as cost, operational complexity, and infrastructure requirements (see Section 1.3).

In addition to operational upgrades, the facility is planning to implement partial diversion of plant effluent from the current outfall on the Santa Fe River to a new outfall on the Rio Grande. This would allow the city to exchange PR WWTP effluent for additional water withdrawals from the Rio Grande without reducing flow in the Rio Grande. The additional diversions for potable water supply would help accommodate anticipated population growth and reduce water supply shortages under projected climate change conditions. The discharge of PR WWTP effluent to the Rio Grande is expected to begin operation in about five years.

The facility also sends a portion of its treated effluent to customers in the city to be used as non-potable water.

1.3 Wastewater Treatment Scenarios

The wastewater treatment scenarios proposed in this study, while mostly derived from the Nutrient Loading and Removal Optimization Study (Carollo Engineers, 2018), were refined in consultation with the project workgroup.[13] The workgroup proposed scenarios based on their relevance to the PR WWTP and their ability to produce differentiated effluent quality and potential environmental impacts. The membrane bioreactor (MBR) with chemical addition (Tier 2) from the Nutrient Loading and Removal Optimization Study was excluded from the list due to

[11] As provided in by 20.6.4.10. NMAC, which is equivalent to a "water quality standard variance" under federal regulations at 40 CFR § 131.14.

[12] As provided in 20.6.4.10 NMAC and 40 CFR 131.11(b)(ii).

[13] The project workgroup consists of members from EPA, the State of New Mexico, the City of Santa Fe, Eastern Research Group (ERG) (contractor to EPA), and Carollo Engineers (Carollo) (contractor to the City of Santa Fe). See Acknowledgements for details.

it producing similar effluent quality to the installation of tertiary treatment with chemical addition (Tier 3) (now Scenario 2 in Table 1-2) but with a higher cost. The final list of proposed scenarios is provided in Table 1-2, with individual scenarios discussed further in Section 2.2. It is important to note that these scenarios are not sequential but standalone alternatives. For example, Scenario 2 is not the result of Baseline plus sidestream filtration (Scenario 1) plus tertiary filtration. Instead, each scenario is a unique process or combination of processes that are added separately to the Baseline configuration.

Table 1-2. Proposed Study Scenarios.

Scenario	Effluent Conc. (mg/L)[a]		Description
	Total Nitrogen	**Total Phosphorus**	
Existing Site Thresholds			
Thresholds	0.42	0.061	See Table 1-1.
Existing Conditions			
Status Quo[b]	5–7	1–5	Based on the analysis of effluent concentrations discussed in Carollo Engineers (2018).
Proposed Scenarios			
Baseline[c]	5	1	The Baseline Scenario refers to the anticipated state of the facility following implementation of all currently planned facility upgrades and partial effluent diversion to the Rio Grande.
Scenario 1 – Sidestream Filtration	4.5	0.7	Scenario 1 refers to the Baseline configuration with the addition of filtrate return flow treatment.
Scenario 2 – Tertiary Filtration	3	0.05	Scenario 2 includes the Baseline configuration with the addition of tertiary deep bed media filters and new chemical feed facilities. Note that Scenario 2 is equivalent to Tier 3 of Carollo Engineers (2018).
Scenario 3 – Reverse Osmosis	2	0.05	Scenario 3 includes the Baseline configuration with the addition of a microfiltration/reverse osmosis system downstream of the secondary clarifiers. Note that Scenario 3 is equivalent to Tier 4 of Carollo Engineers (2018).
Scenario 4 – Zero Discharge (to Santa Fe River)	5	1	Scenario 4 assumes the same facility configurations as the Baseline Scenario, with no discharge to the Santa Fe River. All current effluent discharges to the Santa Fe River would instead be diverted to the Rio Grande, and the city would continue serving its non-potable reuse customers' needs.

[a] Concentrations are estimates of average conditions as provided by Carollo on April 9, 2021. See Table 2-2 for more detailed information.

[b] Effluent concentration ranges from Table 2-3 of Santa Fe, 2018.

[c] When capitalized, "Baseline" refers to the Baseline Scenario. When not capitalized, "baseline" refers to baseline LCA results.

1.4 Metrics and Life Cycle Impact Assessment

Table 1-3 summarizes the metrics assessed for each system configuration, together with the method and units used to characterize each. Abbreviations are included for each metric, which are used throughout this report.

Most of the life cycle impact assessment (LCIA) metrics are estimated using EPA's Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts (TRACI) version 2.1 (Bare, 2012; Bare, 2011). TRACI includes a compilation of methods representing current best practices for estimating ecosystem impacts based on U.S. conditions in conjunction with information from life cycle inventory (LCI) models. Global warming potential (GWP) is estimated in the baseline results using the 100-year characterization factors provided by the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (IPCC, 2013). A sensitivity analysis is presented in Section 4.2 using 20-year GWPs. In addition to TRACI, the ReCiPe LCIA method is used to characterize water depletion and fossil resource use (Huijbregts et al., 2017), impacts which are not included in the current version of TRACI. Water scarcity is evaluated in terms of relative water stress related to water withdrawal using the Available WAter REmaining (AWARE) Method.[14] Cumulative energy demand, including the energy content of all non-renewable and renewable energy resources extracted throughout the supply chains associated with each configuration, is estimated using a method adapted from one provided by the Ecoinvent Centre (Ecoinvent Centre, 2010). Cumulative energy demand is an aggregated reporting of LCI flows associated with energy inputs and, unlike LCIA categories, does not attempt to characterize potential environmental impact.

Toxicity impacts, including human health cancer and noncancer potential and ecotoxicity of waste streams generated under each scenario, are calculated using the USEtox™ model, which is incorporated in TRACI 2.1. EPA's report *Life Cycle and Cost Assessments of Nutrient Removal Technologies in Wastewater Treatment Plants* (U.S. EPA, 2021a) included the evaluation of WWTP-based toxicity impacts derived from metals, disinfection byproducts (DBPs), and trace organics. Like the current study, the primary goal of the prior study was to perform an LCA of WWTPs that provided different levels of nutrient removal; the inclusion of metals, DBPs, and trace organics was done to quantify those systems' ancillary impacts on non-nutrient water quality parameters. Across a range of different treatment systems, metals were shown to have the largest effect on toxicity impact results. Impacts from DBPs were found to be the next most influential (albeit to a far lesser extent than metals), however, the PR WWTP does not chlorinate its effluent, which minimizes the potential for DBP formation. Impacts from toxic organics were found to be small in comparison to metals. Moreover, no site-specific data on toxic organic concentrations are available at the PR WWTP. Therefore, this study only evaluates toxicity impacts derived from metals in order to quantify ancillary impacts or benefits of the study scenarios, following the methodology developed in EPA's nutrient removal LCA report (U.S. EPA, 2021a).

In an LCA, environmental impacts are a function of various air and water emissions (e.g., nitrous oxide) and characterization of those emissions into a common unit that is representative of a potential to cause impact (e.g., nitrous oxide expressed in carbon dioxide equivalents with the potential to cause global warming). Emissions can occur in different environments around the world—they can come from anywhere in upstream supply chain and production processes or they can come from the study system itself. Characterization factors must be able to account for this generality and be geographically or environmentally specific enough to reasonably capture

[14] AWARE scores can be found at the Water Use in Life Cycle Assessment (WULCA) website: https://wulca-waterlca.org/aware/.

the potential for impact. For example, the metrics included in this study quantify potential impacts that can range in geographic scale from global (e.g., GWP and fossil fuel depletion potential) to regional (e.g., smog formation potential, eutrophication potential).

The geographic scale of impacts therefore varies and is not always clearly defined in the LCA. For example, impact categories modeled using EPA's TRACI method rely on U.S. average characterization factors. This means that even though emissions can occur at the local (e.g., burning natural gas at a facility), regional (e.g., burning natural gas at a power plant that feeds into the regional electricity grid), or national (e.g., burning natural gas at multiple factories that manufacture components of a WWTP) scale, the characterization factors used to translate those emissions to potential impacts assume national average conditions. Cumulative energy demand and fossil fuel depletion are inventory metrics that are largely domestic, as the majority of the U.S.'s energy supplies are sourced internally. Water scarcity characterization factors are determined at the watershed[15] level, which is the smallest scale of all Table 1-3 metrics. The three toxicity categories utilize global characterization factors with detailed context information such as "urban air," "rural air," or "indoor air." These contexts communicate information related to human exposure potential of emissions, providing an indirect means of modeling regional impact potential. Additional discussion regarding development methods of each metric is included in Appendix A, while additional discussion of results and their geographic context is provided in Sections 3 and 4.

Table 1-3. Metrics Included in the LCA.

Metric	Abb-reviation	Method	Unit[a]	Description
Eutrophication Potential	EP	TRACI 2.1	kg N eq.	Assesses impacts from excessive load of macro-nutrients to the environment. Important emissions include NH_3, COD and BOD, and N and P compounds. The influence of each compound is translated to an equivalent quantity of nitrogen.
Acidification Potential	AP	TRACI 2.1	kg SO_2 eq.	Quantifies the acidifying effect of substances on their environment. Important emissions: SO_2, NO_X, NH_3, HCl, HF, H_2S.
Cumulative Energy Demand	CED	Ecoinvent	MJ-eq.	Measures the total energy from point of extraction in nature; results include both renewable and non-renewable energy sources.
Global Warming Potential	GWP	IPCC	kg CO_2 eq.	Represents the heat-trapping capacity of greenhouse gases over a 100-year time horizon. Important emissions: CO_2, CH_4, N_2O.
Fossil Fuel Depletion	FFD	ReCiPe	kg oil eq.	Captures the consumption of fossil fuels, primarily coal, natural gas, and crude oil. All fuels are standardized to kg oil eq based on the heating value of the fossil fuel.

[15] Watershed boundaries are based on a global dataset and are unique to the method. They do not necessarily correspond with a specific Hydrologic Unit Code level. For additional information on method development, see Boulay et al. (2018) and Müller Schmied et al. (2014).

Metric	Abb-reviation	Method	Unit[a]	Description
Smog Formation Potential	SFP	TRACI 2.1	kg O_3 eq.	Determines the formation of reactive substances (e.g., tropospheric ozone) that cause harm to human health and vegetation. Important emissions: NO_X, BTX, NMVOC, CH_4, C_2H_6, C_4H_{10}, C_3H_8, C_6H_{14}, acetylene, EtOH, formaldehyde.
Human Health—Particulate Matter Formation	HHPM	TRACI 2.1	kg $PM_{2.5}$ eq.	Results in health impacts such as effects on breathing and respiratory systems, damage to lung tissue, and other human health concerns. Primary pollutants (including $PM_{2.5}$) and secondary pollutants (e.g., SO_X and NO_X) lead to particulate matter formation.
Human Health Toxicity—Cancer Potential	HHC	USEtox™ 2.02	CTUh	The comparative toxic unit (CTU) characterizes the probable increase in cancer related morbidity (from inhalation or ingestion) for the total human population per unit mass of chemical emitted.
Human Health Toxicity—Noncancer Potential	HHNC	USEtox™ 2.02	CTUh	A CTU for noncancer characterizes the probable increase in noncancer related morbidity (from inhalation or ingestion) for the total human population per unit mass of chemical emitted.
Ecotoxicity	ET	USEtox™ 2.02	CTUe	Assesses potential fate, exposure, and effect of chemicals on the environment. Like the human toxicity category, the CTUe unit assesses the potential fraction of species affected (i.e., disappearing) per unit mass of chemical emitted.
Water Scarcity	WS	AWARE	m^3 world equivalents	Scales water depletion results by a range of 0.1 (no water stress at location of withdrawal) to 100 (very high water stress). The water stress factors are based on the available water remaining in a watershed after the demands of humans and the aquatic ecosystem have been met.
Water Depletion	WD	ReCiPe	m^3	Freshwater withdrawals which are evaporated, incorporated into products and waste, transferred to different watersheds, or disposed into the sea after usage.

Table abbreviations: BOD = biochemical oxygen demand; BTX = aromatic hydrocarbons including benzene, toluene and xylene isomers; CH_4 = methane; C_2H_6 = ethane; C_4H_{10} = butane; C_3H_8 = propane; C_6H_{14} = hexane; CO_2 = carbon dioxide; COD = chemical oxygen demand; CTUe = comparative toxicity units for environment; CTUh = comparative toxicity units for humans; eq. = equivalents; EtOH = ethanol; HCl = hydrochloric acid; HF = hydrofluoric acid; H_2S = hydrogen sulfide; m^3 = cubic meter; MJ = megajoules; N = nitrogen; NH_3 = ammonia; NMVOC = non-methane volatile organic compounds; NO_x = Nitrogen oxides; N_2O = nitrous oxide; O_3 = ozone; P = phosphorus; $PM_{2.5}$ = particulate matter 2.5; SO_2 = sulfur dioxide; SO_x = sulfur oxides.

Table Data Source: LCIA characterization factors were drawn from an EPA effort to harmonize flows for the Federal LCA Commons: https://www.lcacommons.gov/lcia-methods-without-flows.

[a] Equivalents refers to characterized impact results, where all pollutants have been transformed to a single unit, or reference substance (e.g., nitrogen equivalents for eutrophication potential), to be on a consistent basis in terms of their contribution to category impacts.

2. LCA METHODOLOGY

This study design follows the guidelines for an LCA provided by the International Organization for Standardization (ISO) standards titled Environmental management—Life cycle assessment—Principles and framework (14040) (ISO, 2006a) and Environmental management—Life cycle assessment—Requirements and guidelines (14044) (ISO, 2006b). The following subsections describe the scope of the PR WWTP study and the functional unit (defined below) used for comparison, as well as the system boundaries, inventory data, and modeling procedure.

2.1 Goal and Scope Definition

2.1.1 Functional Unit

A functional unit is a "quantity of interest" that provides the basis for comparing results in an LCA (e.g., a gallon of treated wastewater). The key consideration in selecting a functional unit is to ensure the wastewater treatment configurations are compared based on equivalent performance. In other words, an appropriate functional unit allows for an "apples-to-apples" comparison. The primary functional unit for this study is the treatment of a cubic meter (m^3) of municipal wastewater such that it meets one of several effluent quality targets. Differentiated effluent qualities are a critical component of the analysis and will be captured in the reported environmental impact results, leading to differentiated environmental performance. Other functional units are used for comparison purposes and are discussed further in Section 3.5.

2.1.2 System Definition and Boundaries

The system boundary includes all relevant details of the wastewater treatment processes, environmental releases from each process, and the supply chains associated with the inputs to each process. The analysis will estimate the impacts of electricity consumption using the electricity mix of Arizona and New Mexico's Emissions & Generation Resource Integrated Database (eGRID) subregion (US EPA, 2020). Chemical use associated with system operation and periodic cleaning of equipment (e.g., membranes) are within the system boundary. The analysis also includes impacts associated with consumable materials used in the filter systems. Environmental impacts associated with release of effluent to the receiving water and brine disposal are also considered.

Production of the influent and the wastewater collection system are excluded from the system boundaries. It is assumed that these elements would be equivalent for all examined treatment configurations and, therefore, can be excluded from the scope of the analysis. Mechanical systems and electronics are excluded from the LCA study boundary due to lack of detailed information. Past analyses have shown the contribution of infrastructure to the overall results of an LCA for a WWTP to be relatively insignificant (Emmerson et al., 1995; Xue et al., 2019). In general, these types of capital equipment are used to treat large volumes of wastewater over a useful life of many years. Thus, energy and emissions associated with producing these facilities and equipment generally become negligible.

Downstream impacts associated with effluent release (i.e., eutrophication and toxicity impacts) are accounted for using the methods and metrics discussed in Appendix A, which quantify the potential for impact. These methods are based on the mass of nutrients or toxic substances released into the environment and their potential to lead to eutrophication or toxicity impacts—they do not account for interactions with the receiving environment, which determine if and how that potential is realized. For the current study, this means that eutrophication and toxicity impacts are based on the mass of pollutants discharged at points of direct effluent release (which include the Santa Fe River and proposed Rio Grande discharges) as well as any emissions associated with processes at the WWTP or the supply chains of inputs to the processes.

Flow diagrams of system boundaries for each scenario are provided in Section 2.2.2. As previously noted, the proposed scenarios in this study were selected based on their relevance to the PR WWTP and their ability to produce differentiated effluent quality and potential environmental impacts. Although only 4 scenarios (plus baseline) were evaluated, they represent a range of environmental outcomes that will provide insights to potential intermediary options (i.e., between the baseline and reverse osmosis).

2.2 Life Cycle Inventory

2.2.1 Introduction

An LCI is a comprehensive list of inputs and outputs to and from the system across the entire life cycle of the product or process. It accounts for the flows to and from nature (e.g., emissions to air, water discharges) and between related processes in the technosphere (e.g., material and energy requirements) for each process in the assessed life cycle (ISO, 2006b). The LCI for the Baseline Scenario is based on historical, average conditions of the PR WWTP, as well as estimates of changes that may occur due to upgrades that are currently being installed. Operational calculations are based on average annual data (where available) and standardized to a cubic meter basis using the total volume of water treated in the years for which data are available. Environmental impacts of infrastructure are allocated to wastewater treated over the lifetime of individual components.

LCI data are the foundation of any LCA study. Every element included in the analysis is modeled as its own LCI unit process entry. The connection of LCI unit process data constitutes the LCA model. A simplified depiction of a subset of this structure for this study is shown in Figure 2-1. The overall system boundaries include all unit processes associated with plant operations and disposition of sludge. Each box in the figure represents an LCI unit process. The full system is a set of nested LCIs where the primary outputs (in red) of one process serve as inputs (in blue) to another process. Within each nested level, there can be flows both to and from the environment. Flows from the environment are written in orange in Figure 2-1 and are represented by the thin black arrows crossing the system boundary from nature. Emissions to the environment are listed in green, and these flows are tabulated in the calculation of environmental impacts. Intermediate inputs (in blue) are those that originate from an extraction or manufacturing process within the supply chain.

The distinction between the foreground and background systems is not a critical one. The foreground system tends to be defined as those LCIs that are the focus of the study. In this case, that is the WWTP itself. Background LCI information is comprised of extractive and manufacturing processes that create material and energy inputs required by the wastewater treatment systems.

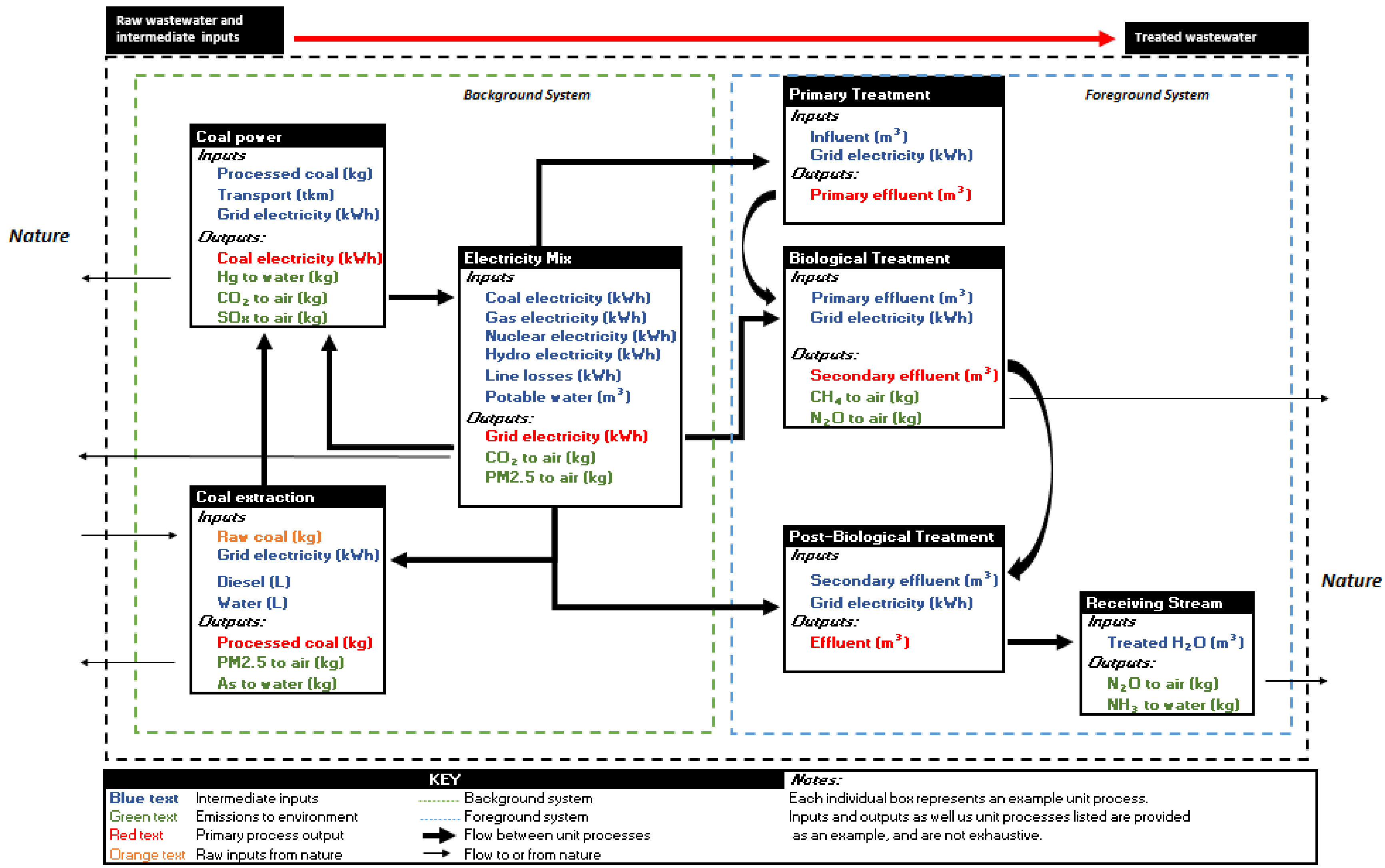

Figure 2-1. Subset of LCA model structure with example unit process inputs and outputs.

2.2.2 Foreground LCI Data

As discussed earlier, the foreground system for this study is defined as the PR WWTP itself. For each of the five wastewater treatment configurations evaluated, PR WWTP staff or their consulting engineers (Carollo Engineers) provided foreground information. The foreground LCI unit process data developed for this study for all levels are summarized in Appendix B in Table B-1 through Table B-5. All data collected for this study were subject to quality assurance project plan (QAPP; available upon request from EPA) requirements for completeness, representativeness, accuracy, and reliability. A description of overall data quality results for the LCI is provided in Appendix D.

Table 2-1 provides an overview of the foreground unit processes that make up each of the wastewater treatment configurations evaluated in this study. Many unit processes are common to all configurations with inputs and outputs remaining consistent across scenarios. Scenarios are primarily differentiated based on additional sidestream or tertiary unit processes. Energy demand and process GHG emissions (introduced in Section 2.2.3.1) of the biological treatment process are adjusted to consider lower nutrient and biochemical oxygen demand (BOD) loading resulting from installation of sidestream treatment in Scenario 1. Operation of secondary treatment processes for Tertiary Filtration, Reverse Osmosis and Zero Discharge (Scenarios 2, 3, and 4) are consistent with Baseline performance. Sludge and biogas production and treatment are expected to remain consistent across scenarios but are assessed in sensitivity and uncertainty assessments.

Energy, chemical, and material inputs (e.g., background unit processes) to each of the unit processes are tracked in terms of energy, mass, or volume units. Releases to air and water for each unit process are tracked together with information about the environmental compartment to which they are released to allow for appropriate impact characterization. Waste streams are connected to supply chains associated with providing waste management services, such as landfilling.

Table 2-1. Foreground Unit Processes Included in Each Wastewater Treatment Configuration.

Unit Process	Wastewater Treatment Configuration				
	Baseline (B)	Scenario 1 B + Sidestream Filtration	Scenario 2 B + Tertiary Filters	Scenario 3 B + Reverse Osmosis	Scenario 4 B + Zero Discharge (Full Diversion[a])
Core facility	✓	✓	✓	✓	✓
Preliminary treatment: screening and grit removal	✓	✓	✓	✓	✓
Secondary treatment: biological	✓	✓	✓	✓	✓
Tertiary treatment: disk filtration	✓	✓			✓
Sidestream treatment: filtrate		✓			
Tertiary treatment: deep bed media filters			✓		
Tertiary treatment: microfiltration				✓	
Tertiary treatment: reverse osmosis				✓	

Unit Process	Wastewater Treatment Configuration				
	Baseline (B)	**Scenario 1 B + Sidestream Filtration**	**Scenario 2 B + Tertiary Filters**	**Scenario 3 B + Reverse Osmosis**	**Scenario 4 B + Zero Discharge (Full Diversion[a])**
Chemical post-treatment				✓	
Disinfection: ultraviolet	✓	✓	✓	✓	✓
Wastewater treatment plant (WWTP) effluent: discharge	✓	✓	✓	✓	
WWTP effluent: reuse	✓	✓	✓	✓	✓
WWTP effluent: partial diversion[a]	✓	✓	✓	✓	
WWTP effluent: full diversion[a]					✓
Sludge: dissolved air flotation	✓	✓	✓	✓	✓
Sludge: anaerobic digestion	✓	✓	✓	✓	✓
Sludge: belt filter press	✓	✓	✓	✓	✓
Sludge: landfilling	✓	✓	✓	✓	✓
Sludge: composting	✓	✓	✓	✓	✓
Sludge: land application	✓	✓	✓	✓	✓
Biogas: cleaning	✓	✓	✓	✓	✓
Biogas: flaring	✓	✓	✓	✓	✓
Biogas: boiler	✓	✓	✓	✓	✓
Biogas: combined heat and power	✓	✓	✓	✓	✓
Brine: underground inject				✓	

✓ Indicates the unit process is relevant for select wastewater treatment configuration.

[a] Refers to full diversion of PR WWTP effluent from the primary discharge point in the Santa Fe River to the secondary outfall in the Rio Grande.

Detailed water quality data were compiled from a range of sources, including historical monitoring data from the PR WWTP, estimates of anticipated treatment performance made by Carollo Engineers, and treatment performance from similar systems. Table 2-2 summarizes influent and effluent water qualities used for this study. Influent data are based on historic (2015–2020) data and are mainly illustrated for comparison purposes; they are only used for calculations discussed in Section 3.5.3. Effluent data for organics and nutrients are based on performance estimates provided by Carollo for each of the treatment configurations. For metals, this study assumes past performance, as measured by 2015–2020 observed effluent quality, to be representative of the Baseline configuration. This study assumes Scenario 1 would have a negligible effect on metals removal and uses performance data from similar systems to estimate metals removal by Scenarios 2 and 3, as discussed further in Appendix E.

Table 2-2. Influent and Estimated Effluent Water Quality for each Wastewater Treatment Configuration.

Parameter	Influent[a]	Baseline/Scenario 4 – Zero Discharge		Scenario 1 – Sidestream Filtration[d, e]		Scenario 2 – Tertiary Filters[e, h]		Scenario 3 – Reverse Osmosis[e, i]	
	Value	Value	Range	Value[b]	Range[c]	Value[b]	Range[c]	Value[b]	Range[c]
Organics and Nutrients, mg/L									
Total suspended solids (TSS)	353	5.0	<10	5	<10	5	<10	3	<5
Volatile suspended solids (VSS)	NA	3.5	<1	3.5	<1	3.5	<1	2.1	<4
carbonaceous biochemical oxygen demand (5-day) (cBOD5)	340	5.0	<10	5	<10	3	<5	3	<5
Chemical oxygen demand (COD)	1015	30	<50	30	<50	20	<30	20	<30
Total Kjeldahl nitrogen (TKN)	78.6	3.5	<5	3	<5	2.5	<3	1.5[g]	<3
Nitrate/nitrite[j]	NA	1.5	NA	1.5	NA	0.5	NA	0.43	NA
Total nitrogen (TN)	78.6	5.0	<10	4.5	<7	3	<5	2	<5
Organic nitrogen (Org-N)[k]	28.1	2.5	<3	2.5	<3	2.5	<3	1.5	<2
Ammonium-nitrogen (NH4-N)	50.5	0.1	<1	0.1	<1	0.1	<1	0.1	<1
Total phosphorus (TP)	13.8	1.0	<2.5	0.7	<1	0.05[f]	<0.1[f]	0.05	<0.2
Orthophosphate (OP)	NA	0.1	<0.2	0.05	<0.2	0.02[g]	<0.05[g]	0.02	<0.2
Metals, µg/L[k]									
Arsenic	3.0	1.0	0–200	1.0	0–200	0.90	0–180	0.10	0–20
Cadmium	0.21	0.021	.021–0.20	0.021	.021–0.20	0.019	0.019–0.18	0.00021	
Chromium	1.6	0.045	0.045–100	0.045	0.045–100	0.045	0.045–100	0.045	0.045–100
Copper	103	4.0	2.1–39	4.0	2.1–39	3.4	1.8–33	0.24	0.13–2.3
Lead	2.6	0.34	0.20–192	0.34	0.20–192	0.27	0.16–150	0.0034	0.0020–1.9

Parameter	Influent[a]	Baseline/Scenario 4 – Zero Discharge		Scenario 1 – Sidestream Filtration[d, e]		Scenario 2 – Tertiary Filters[e, h]		Scenario 3 – Reverse Osmosis[e, i]	
	Value	Value	Range	Value[b]	Range[c]	Value[b]	Range[c]	Value[b]	Range[c]
Mercury	0.082	0.0019	8E-4–2.7	0.0019	8E-4–2.7	1.73E-03	7E-4–2.4	0.00010	4E-4–0.14
Nickel	4.6	2.5	1.3–6.2	2.5	1.3–6.2	2.4	1.3–6.0	0.23	0.12–0.56
Silver	1.7	0.015	0.015–0.34	0.015	0.015–0.34	0.015	0.015–.34	0.015	0.015–0.34
Zinc	165	64.9	0–118	64.9	0–118	46.1	0–84	1.9	0–3.5

Table abbreviations: NA = not available.

[a] Average of 2020 PR WWTP data.

[b] Expected average annual effluent quality.

[c] Can be +/- % or concentration range.

[d] Sidestream filtration assumes aeration system improvements are in place and includes filtrate return flow treatment for nitrogen removal (DEMON® Annamox) and phosphorus removal (AirPrex®/MagPrex™ from digestate).

[e] These are estimated values based on experience from other similar installations. These values are not to be understood as technology performance guarantees.

[f] This indicates limit of technology. Concentrations depend on chemical dose addition.

[g] Estimated. Depends largely on size distribution of soluble organic nitrogen (unknown).

[h] Assumes tertiary nitrogen and phosphorus filters in series. Assumes that sidestream treatment for nitrogen and phosphorus removal (Scenario 1) would not be installed in this scenario.

[i] Assumes microfilter and reverse osmosis treatment downstream of secondary treatment. Assumes that sidestream treatment for nitrogen and phosphorus removal (Scenario 1) and tertiary filtration for nitrogen and phosphorus removal (Scenario 2) would not be installed.

[j] Calculated as the difference between TKN and NH4-N.

[k] Influent and Baseline effluent concentrations determined from historic (2015–2020) metals data. See Appendix E for methods to determine removal rates from Scenarios 1–4.

2.2.2.1 Baseline Scenario – Planned Upgrades

The PR WWTP is in the process of upgrading and expanding several system components, including the existing biological treatment process for enhanced nutrient removal and process control, and the capacity of their anaerobic digesters. The PR WWTP is also adding a combined heat and power (CHP) system to convert methane produced by the digesters into usable heat and electricity. Figure 2-2 shows the layout of the wastewater treatment facility, which reflects the anticipated state following all currently planned upgrades.

Preliminary treatment at the PR WWTP includes bar screens and aerated grit traps. Collected grit and screenings are trucked offsite to the local landfill. Primary clarifiers precede the plant's biological process, which includes an optional anoxic selector preceding a pair of aeration basins that are configured as "four-pass carrousel oxidation ditches" (Carollo Engineers, 2018). Primary effluent is blended with return activated sludge, mixed liquor, filtrate, and dissolved air flotation (DAF) underflow before secondary treatment. Secondary effluent is treated with disc filters prior to ultraviolet (UV) disinfection, post-aeration, and release.

Currently, most wastewater effluent is discharged to the Santa Fe River. However, the municipality is proceeding with a plan to build a diversion pipeline to route most of the PR WWTP effluent to the Rio Grande (see Section 1.2 for additional discussion). The city does not know exactly how much effluent will eventually be diverted. The Baseline Scenario (as well as Scenarios 1–3) assumes that an annual average flow of 1 MGD (range of 0.5–2 MGD) will be diverted to the Rio Grande, with the remainder continuing to satisfy existing non-potable reuse demand or to be discharged to the Santa Fe River. Actual daily diversion flows will vary seasonally, with more diversion occurring in the winter months. The diversion flow rate (1 MGD) is an assumed value for the purposes of conducting this LCA, as the city is still conducting planning and permitting efforts and has not committed to any particular flow.

The PR WWTP pumps a portion of its treated effluent offsite for non-potable reuse as irrigation water, which defers pumping and consumption of 0.127 m^3 of groundwater per m^3 of treated effluent after accounting for volume losses during treatment. Although this water reuse is seasonal, as it is used mainly for irrigation purposes, this study accounts for the reuse flow on an average annual basis. Offsite pumping of non-potable water for reuse requires an estimated 0.075 kilowatt hours per cubic meter (kWh/m^3) of treated wastewater and avoids 0.028 kWh of electricity that would be used to pump groundwater, leading to a net increase in electricity demand. Emission of nutrients, chemical oxygen demand (COD), and metals that would otherwise have been emitted to surface water with the rest of treatment plant effluent are instead applied to land in the irrigation water. No avoided fertilizer benefit is assessed for the reused water.

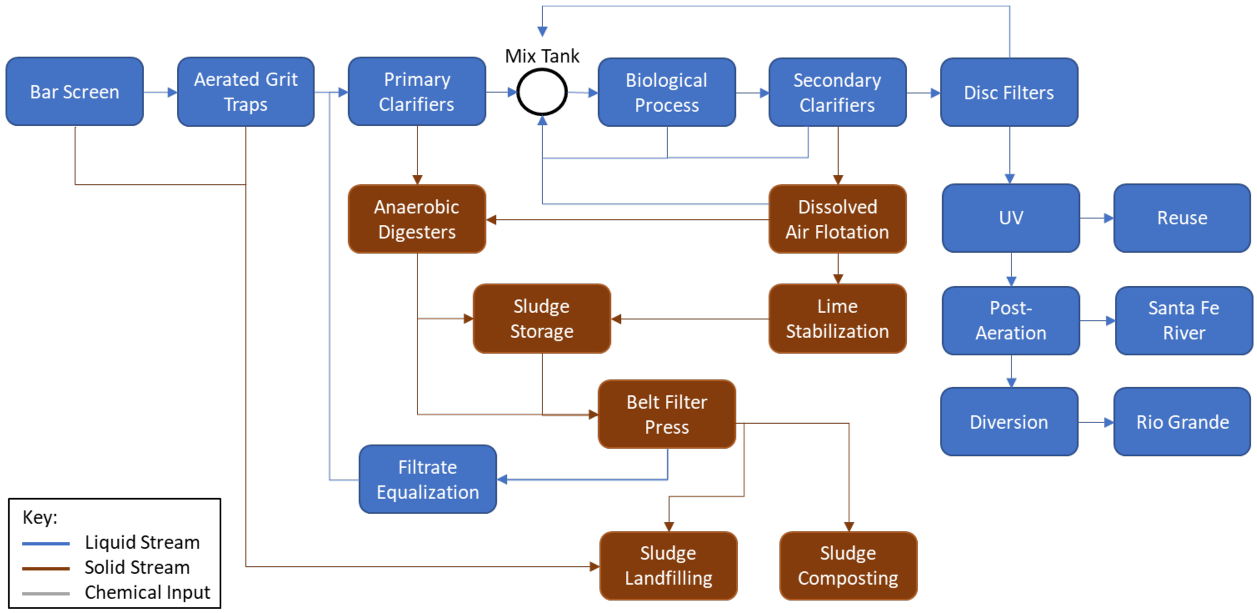

Figure 2-2. System diagram of the existing PR WWTP following upgrades to the biological treatment system.

Waste activated sludge from the secondary clarifiers is thickened in a DAF process and mixed with primary solids before anaerobic digestion. A portion of sludge is stabilized using lime addition. Digestate is thickened in a belt filter press (BFP) and stabilized in an onsite windrow composting facility (50% of digestate) with regional green waste or is sent to the local landfill (50% of digestate). Section 2.2.3 briefly describes the scope of air emissions modeling performed for each process. The quantity of digestate produced and its fate is consistent across scenarios. LCI data for these processes are available in Table B-1.

The PR WWTP installed a CHP system as part of their plant upgrades. Biogas produced in the anaerobic digesters is combusted onsite in the CHP engines, boilers, or flares, as illustrated in Table 2-3. The facility provided emissions data for the combustion processes for nitrogen oxides (NO_X), carbon monoxide (CO), and volatile organic compounds (VOCs), as reported in Table B-1. Another LCA considering beneficial use of anaerobic digestion biogas was used to provide supplementary estimates of other air emissions for the CHP engines, boiler, and flare (Morelli et al., 2019).

Table 2-3. Allocation of Biogas to Onsite Combustion Processes.

Combustion Process	Baseline Value	Minimum Value	Maximum Value
Combined heat and power engine	83%	74%	95%
Boiler	15%	2.1%	24%
Flare	1.9%	1.9%	2.9%

2.2.2.2 Scenario 1 – Sidestream Filtration

Figure 2-3 shows the WWTP layout for Sidestream Filtration (Scenario 1). Operation of preliminary, primary, secondary, and sludge treatment processes remain the same in Sidestream Filtration (Scenario 1) as in the Baseline Scenario (Section 2.2.2.1). Additional nitrogen and phosphorus removal is achieved by installing equalization and sidestream treatment processes on the flow of BFP filtrate before it returns to secondary treatment. DEMON® Anammox and the MagPrex™ struvite processes are used to remove ammonia and phosphorus from the filtrate return flow, respectively. A magnesium chloride salt is added to the filtrate to precipitate phosphorus as struvite. Struvite is assumed to be used as an agricultural fertilizer displacing the production of diammonium phosphate (DAP). Both processes require additional electricity consumption. Filtrate treatment reduces the load of nitrogen to secondary treatment, however, the emission of nitrous oxide from the DEMON® process is similar to those of conventional nitrification/denitrification biological processes (Weissenbacher et al., 2010). LCI data for Sidestream Filtration (Scenario 1) are available in Table B-2.

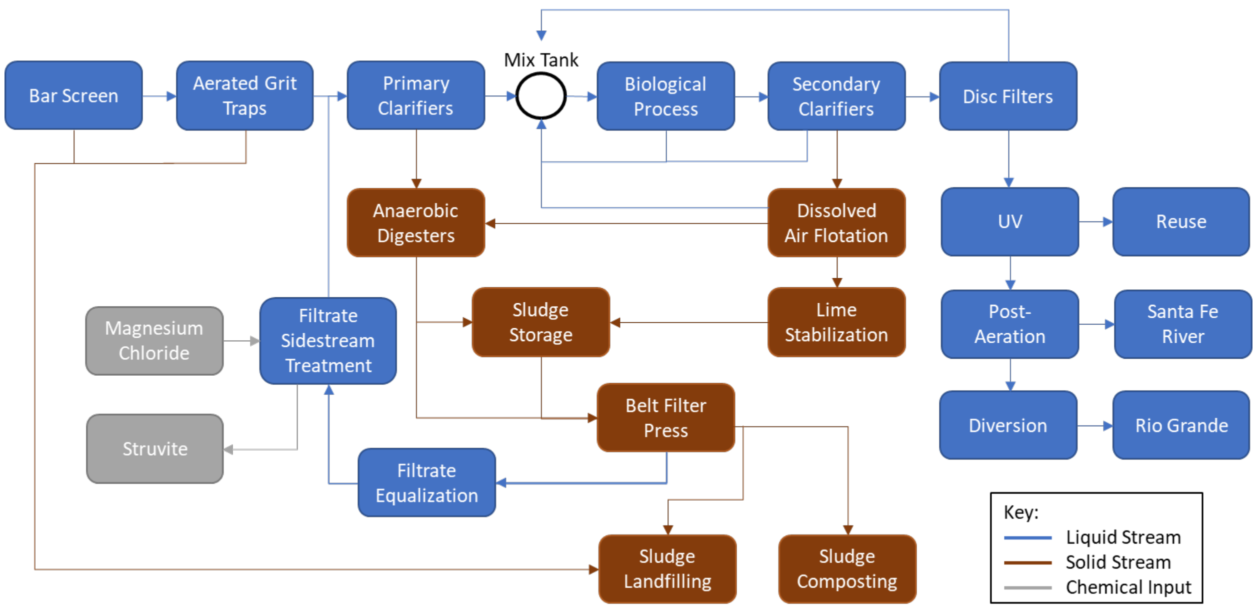

Figure 2-3. System diagram of Scenario 1 – Sidestream Filtration.

2.2.2.3 Scenario 2 – Tertiary Filtration

Figure 2-4 shows the WWTP layout for (Scenario 2). Operation of preliminary, primary, secondary, and sludge treatment processes remain the same in Scenario 2 as in the Baseline Scenario (Section 2.2.2.1) with the exception of disc filtration, which would be eliminated. In this scenario, additional nitrogen and phosphorus removal are achieved through the installation of sequential deep-bed media filters. Methanol is added to secondary effluent before the first deep-bed media filter to assist in denitrification. Alum is added for the removal of phosphorus in the second filter. Additional pumping energy is required to move wastewater through the filters. The effect of filter operation on secondary treatment processes is assumed to be negligible. LCI data for these processes are available in Table B-3.

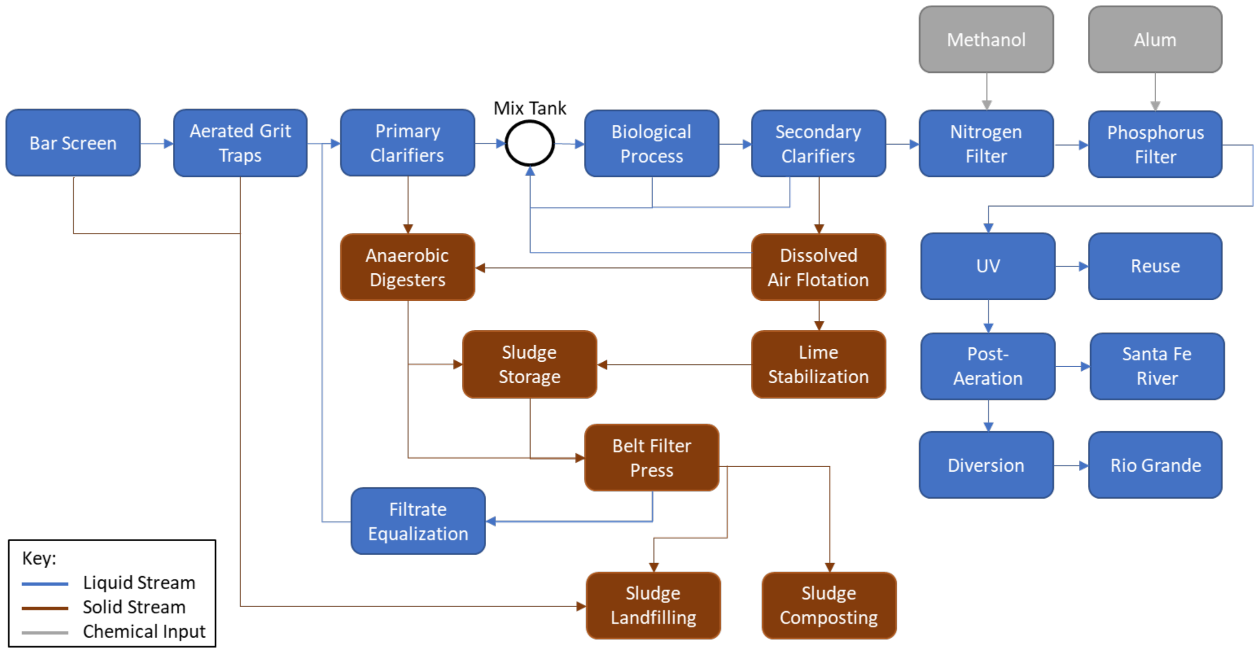

Figure 2-4. System diagram of Scenario 2 – Tertiary Filters.

2.2.2.4 Scenario 3 – Reverse Osmosis

Figure 2-5 shows the WWTP layout for Reverse Osmosis (Scenario 3). Operation of preliminary, primary, secondary, and sludge treatment processes remain the same in Reverse Osmosis (Scenario 3) as in the Baseline Scenario (Section 2.2.2.1) with the exception of disc filtration, which would be eliminated. Additional nitrogen and phosphorus removal are achieved through installation of an RO filter. A microfilter (MF) is also installed before RO to reduce fouling and prevent membrane damage. The total quantity of MF and RO membrane units are installed based on a design flow of 9 MGD and the production of 2 MGD of brine relative to a total facility design flow of 12 MGD. The remaining 25% of design flow bypasses the MF/RO process.

Carbon dioxide and sodium bisulfite are added to the wastewater in a chemical post-treatment process. Of the 9 MGD of wastewater treated by the MF/RO process under design conditions, 2 MGD becomes brine and is disposed of via onsite deep well injection. Based on discussions with PR WWTP staff and their consulting engineers, other options for disposal of RO brine, such as mechanical or pond evaporation, are less feasible for this project and are not modeled in this analysis. LCI data for these processes are available in Table B-4.

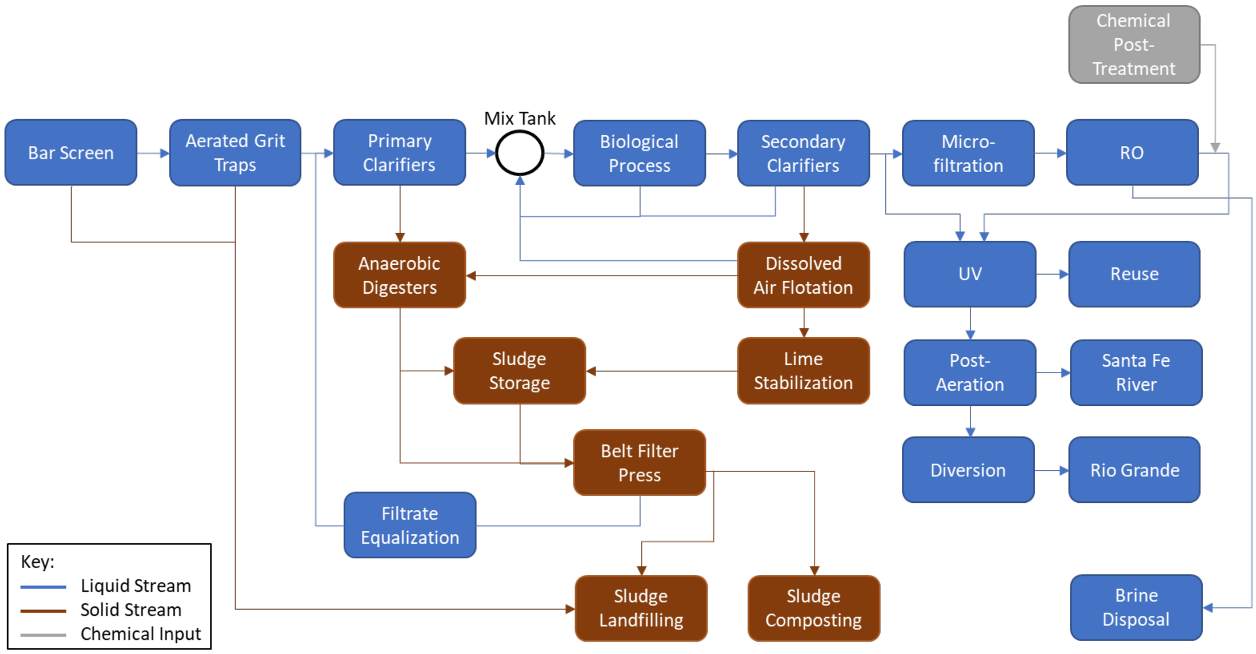

Figure 2-5. System diagram of Scenario 3 – Reverse Osmosis.

2.2.2.5 Scenario 4 – Zero Discharge to Santa Fe River

Figure 2-6 shows the WWTP layout for Zero Discharge (Scenario 4). Operation of all treatment processes remain the same in Scenario 4 as in the Baseline Scenario (Section 2.2.2.1). Effluent discharge (the portion that is not pumped to non-potable reuse customers) is diverted completely to the Rio Grande via pipeline, with no discharge into the Santa Fe River. Partial diversion of effluent to the Rio Grande is included in all scenarios, and the necessary infrastructure to achieve full diversion will be installed regardless of the quantity of effluent ultimately diverted (PVC piping for the pipeline, which will be 30-inch pressure pipe, is included in all scenarios). Increased electricity demand for additional effluent pumping is the only additional requirement for the full diversion scenario. LCI data for this process are available in Table B-5.

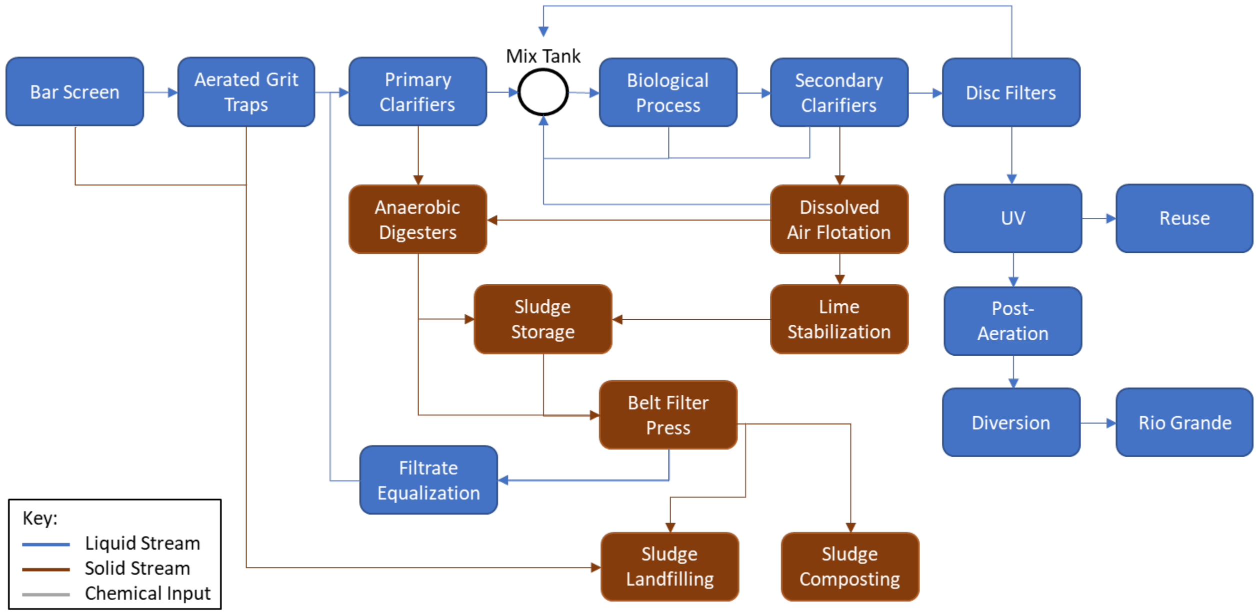

Figure 2-6. System diagram of Scenario 4 – Zero Discharge to Santa Fe River.

2.2.3 LCI Background Data Sources

The supply chains of inputs to the wastewater treatment processes are represented where possible using publicly available data from the Federal LCA Commons (Federal LCA Commons, 2021). Within the Federal LCA Commons, background material, fuel, and transport datasets are sourced from the National Renewable Energy Laboratory's U.S. LCI database (NREL, 2019). Where required background datasets were not available from the Federal LCA Commons, the Ecoinvent version 3.7 database is used (Frischknecht et al., 2005). Ecoinvent is a widely used global LCI database available by paid subscription. Table 2-4 lists background unit processes used in the LCA model and their source databases. The environmental flow inputs and outputs for the selected background databases were harmonized using EPA's Federal LCA Commons Elementary Flow List (Edelen et al., 2019). Using this standardized list ensures that all the environmental flows in the LCA are properly captured in the impact assessment results.

Table 2-4. Background Unit Process Data Sources.[a]

Background Input	Original Unit Process Name	LCI Database
Alum	Aluminum sulfate production, powder | aluminum sulfate, powder | Cut-off, S	Ecoinvent 3.7
Carbon dioxide	Carbon dioxide production, liquid | carbon dioxide, liquid | Cut-off, S	Ecoinvent 3.7
Citric acid	Citric acid production | citric acid | Cut-off, S	Ecoinvent 3.7
Fertilizer, nitrogen	Urea production | urea | Cut-off, S	Ecoinvent 3.7
Fertilizer, nitrogen and phosphorus	Diammonium phosphate production | diammonium phosphate | Cut-off, S	Ecoinvent 3.7
Fertilizer, phosphorus	Single superphosphate production | single superphosphate | Cut-off, S	Ecoinvent 3.7
Fertilizer, potassium	Potassium sulfate production | potassium sulfate | Cut-off, S	Ecoinvent 3.7

Table 2-4. Background Unit Process Data Sources.[a]

Background Input	Original Unit Process Name	LCI Database
Filter nozzles, steel	Casting, steel, lost-wax | casting, steel, lost-wax | Cut-off, S Steel production, chromium steel 18/8, hot rolled | steel, chromium steel 18/8, hot rolled | Cut-off, S	Ecoinvent 3.7
Membrane, microfilter/reverse osmosis	Polyvinylfluoride production | polyvinylfluoride | Cut-off, S	Ecoinvent 3.7
Phosphoric acid	Phosphoric acid production, dihydrate process | phosphoric acid, fertilizer grade, without water, in 70% solution state | Cut-off, S	Ecoinvent 3.7
Polymer	Polyacrylamide production | polyacrylamide | Cut-off, S	Ecoinvent 3.7
Proprietary cleaning solution	Citric acid production | citric acid | Cut-off, S	Ecoinvent 3.7
Residuals to landfill	Treatment of inert waste, inert material landfill | inert waste, for final disposal | Cut-off, S	Ecoinvent 3.7
Sodium hypochlorite	Sodium hypochlorite production, product in 15% solution state | sodium hypochlorite, without water, in 15% solution state | Cut-off, S	Ecoinvent 3.7
Electricity	Electricity, AC, 120 V (from 2019 AZNM grid)	eLCI
Anthracite	Anthracite coal, at mine	USLCI
Caustic soda	Sodium hydroxide, production mix, at plant	USLCI
Diesel, combusted	Transport, passenger truck, diesel powered Diesel, combusted in industrial equipment	USLCI
Filter pads, polyester	Unsaturated polyester, UPR, resin, at plant	USLCI
Gravel	Gravel, at mine	USLCI[b]
Lime	Quicklime, at plant	USLCI
Methanol	Methanol, at plant, kg	USLCI
Natural gas, anaerobic digestion	Natural gas, combusted in industrial boiler	USLCI
Natural gas, compost	Natural gas, combusted in industrial equipment, 1.357 m^3/kg, 52.13 MJ/kg	USLCI
Sand	Sand, at mine	USLCI[b]
Sulfuric acid	Sulfuric acid, at plant	USLCI

[a] The label "Cut-off, S" refers to system processes from Ecoinvent's cut-off system model. A system process aggregates all allocated upstream and process elementary flows within an single inventory, providing confidentiality for upstream data providers and data portability for LCA practitioners. System models refer to treatment of recycled content across life cycles. In the cut-off system model, the environmental impacts of material extraction and processing are allocated to the material's first user, allowing recycled material to enter subsequent life cycles without environmental burden.

[b] Adapted from USLCI's limestone mining unit process.

Electricity is a key background unit process for all the wastewater treatment configurations investigated. Table 2-5 displays the Arizona/New Mexico (AZNM) subregion generation resource mix applied in the foreground LCA model and the U.S. average generation resource mix used in the electricity sensitivity analysis (U.S. EPA, 2021b). The AZNM resource mix provides 83% of the electricity for the AZNM consumption mix used in the analysis. The remaining 17% of consumed electricity is provided by neighboring exporting regions.

Consumption mixes consider trading that occurs due to grid complexity, and is expected to provide a more accurate estimate of environmental impact associated with grid-based electricity consumption in eGRID subregions (Hottle and Ghosh, 2021). These data are based on eGRID resource mix information from 2019 and were generated using EPA's Electricity LCI (eLCI) tool within the Federal LCA Commons (U.S. EPA, 2020a). A loss factor of 5.3% is applied to account for electricity losses during distribution to the final consumer (i.e., PR WWTP). Section 4.4 presents a sensitivity analysis for the electricity used by the facility, modeling a scenario that uses U.S. average electricity, as well as a scenario that uses 100% solar electricity, to meet the WWTP electricity requirements.

Table 2-5. Arizona/New Mexico Average Electrical Grid Mix.

Fuel	Regional Grid (%)	U.S. Average Grid (%)
Natural gas	44.9%	38.4%
Coal	22.3%	23.3%
Nuclear	18.8%	19.6%
Solar	4.50%	1.74%
Geothermal	3.60%	0.37%
Hydro	3.10%	6.83%
Wind	2.20%	7.15%
Biomass	0.40%	1.56%
Oil	0.10%	0.61%
Other	0%	0.44%

2.2.3.1 Biogas Cleaning

Basic biogas cleaning processes, including iron sponge scrubbing, moisture removal, compression, and siloxane removal, are modeled for the portion of biogas combusted in the onsite boiler and CHP engines. Iron sponge scrubbing uses iron oxide impregnated-wood chips to remove hydrogen sulfide (H_2S) from produced biogas. Iron oxide media can be regenerated several times by air purging, releasing adsorbed H_2S as elemental sulfur. Modeling assumes that the concentration of H_2S is reduced from 500 (Wiser et al., 2010) to 1 part per million volume (Ong et al., 2017). The process requires electrical energy to circulate air for the media regeneration step. Spent media is disposed of in an inert material landfill. Moisture is removed from produced biogas by chilling and condensation, assuming an electrical energy requirement equivalent to 2% of produced biogas energy content (Ong et al., 2017). Biogas is compressed to 4 pounds per square inch gauge prior to combustion. Siloxane removal using activated carbon is the final biogas cleaning step. The quantity of activated carbon required for siloxane adsorption is estimated assuming a biogas siloxane content of 100 milligrams per cubic meter and a mass loading rate of 10% (siloxane mass/activated carbon mass). Table 2-6 presents LCI data for the biogas cleaning processes. Biogas production and cleaning is consistent across the considered scenarios.

Table 2-6. Life Cycle Inventory Data for Biogas Cleaning.

Process Name	Input Name	Mean Value	Units[a]
Biogas cleaning—iron sponge	Electricity	3.5E-5	kWh/m^3
	Iron sponge	5.4E-4	kg/m^3
Biogas cleaning—moisture removal	Electricity	0.04	kWh/m^3
Biogas cleaning—compression	Electricity	3.4E-3	kWh/m^3
Biogas cleaning—siloxane removal	Activated carbon	3.5E-4	kg/m^3

[a] Biogas cleaning inventory data is normalized to the average annual flow of wastewater treated at the PR WWTP.

2.2.3.2 Digestate Composting

Half of produced digestate is composted with yard waste at an onsite windrow composting facility. The facility reports that approximately 0.39 kilogram (kg) of yard waste is composted per kg of digestate. The LCI for the composting process includes electricity and natural gas consumption and process emissions of ammonia, carbon monoxide, methane, nitrous oxide, and non-methane volatile organic compounds. Only process emissions attributable to the digestate are included in the LCA model, as yard waste is a separate material and its emissions are not attributable to the wastewater system. Characteristics of the digestate, yard waste, and finished compost (presented in Table 2-7) are used to estimate process emissions. Compost is produced in an indoor facility and leachate production is assumed to be negligible. LCI data for the compost process is available in Table B-1. Digestate production and composting is consistent across the considered scenarios.

Table 2-7. Characteristics of Digestate, Yard Waste, and Finished Compost.

Characteristic	Digestate	Yard Waste[c]	Compost	Units
Moisture content	87%[a]	48%	32%[d]	% of wet mass
Nitrogen content	5.8%[a]	1.5%	2.4%[d]	% of dry mass
Phosphorus content	1.9%[b]	0.20%	0.90%[e]	% of dry mass
Potassium content	3.1%[b]	1.3%	0.48%[f]	% of dry mass
Carbon content	41%[b]	43%	36%[d]	% of dry mass

[a] PR WWTP average values for 2020.

[b] (Nkoa, 2014).

[c] (Yoshida et al., 2012).

[d] PR WWTP compost chemical analysis for 2019.

[e] (Morelli et al., 2019).

[f] (Keng et al., 2020).

2.2.3.3 Compost Land Application

Finished compost is a Class A material that is assumed to be sold locally and used as a soil amendment on home gardens or agricultural crops (U.S. EPA, 2002). The LCA model assumes that using compost in these applications displaces the use of chemical fertilizers such as urea, single superphosphate, and potassium sulfate, based on the nitrogen, phosphorus, and potassium content of the compost (Table 2-7). Nutrients in organic amendments, such as compost, are typically less plant-available than similar quantities of nutrients in chemical fertilizers (Rigby et al., 2016). Fertilizer substitution rates are applied to estimate the quantity of plant-available nutrients in land-applied compost that can reasonably be assumed to displace the production and use of chemical fertilizers. Average fertilizer substitution rates of 30%, 73%, and 80% were used for nitrogen, phosphorus, and potassium respectively (see Table B-1 for more information).

The analysis assumes that 12% of land-applied carbon is sequestered beyond the 100-year time horizon considered in the baseline LCA model based on literature values indicating a range of between 9% (Boldrin et al., 2009) and 15% (Yoshida et al., 2012). The model also includes estimates of emissions to air and water that would accompany land application of composted digestate. These emissions are assumed to be similar in magnitude to emissions that would result from use of chemical fertilizers, leading to no net change in agricultural emissions. These emissions are included in the analysis to demonstrate their scale relative to other aspects of the system. LCI data for the land application process is available in Table B-1. Compost land application is consistent across the considered scenarios.

2.2.3.4 Digestate Landfilling

Half of produced digestate is trucked offsite (64 km) and disposed of in the local landfill. The landfill's gas capture system is assumed to have the national average gas capture rate of 68.2% over the facility's lifespan. The landfill does not have an energy recovery system and flares the captured landfill gas. Emissions data from the biogas flare are used to estimate flare emissions (Table B-1). A first order decay equation is used to estimate the quantity of degradable carbon that is converted to methane over the 100-year analysis period as a function of the values reported in Table 2-8. Produced methane that is not captured, and either flared or oxidized in the landfill cover, is released to the atmosphere. Non-degradable carbon and the fraction of degradable carbon that is not decomposed within the 100-year analysis period are sequestered, providing a climate benefit. Leachate treatment and emissions are included in the LCA model based on LCI data from (Righi et al., 2013). Leachate is assumed to be produced at a rate of 145 liters per metric ton of organic waste landfilled. LCI data for the landfill and leachate treatment process is available in Table B-1. Digestate landfilling is consistent across the considered scenarios.

Table 2-8. Key Landfill Modeling Parameters.

Parameter	Value	Units	Source
Landfill gas capture rate	68%	% of produced gas	"Typical collection" for decay factor of 0.02 (U.S. EPA, 2020b).
Degradable organic carbon (DOC)	5%	% of wet mass	(RTI International, 2010).
Non-degradable organic carbon	0.4%	% of wet mass	Calculated based on digestate DOC and carbon content in Table 2-7.
Fraction of degradable carbon decomposed (DOCf)	65%	% of DOC	(SYLVIS, 2011)
Decay factor (k)	0.02	unitless	Factor for arid area (LandGEM).

Parameter	Value	Units	Source
Fraction of degraded carbon converted to methane	50%	% of decomposed carbon	(RTI International, 2010).
Oxidation factor	10%	% of produced methane	(IPCC, 2006).

2.2.4 Process GHG Emission Estimation Methodologies

Estimates of onsite, process-based GHG emissions are made for methane (CH_4) production from biological treatment, anaerobic digestion, and landfill disposal of biosolids. Estimates of nitrous oxide (N_2O) emissions from biological treatment and receiving waters are also included in the analysis (IPCC, 2006). Carbon dioxide (CO_2) emissions from wastewater treatment processes are not included in the inventory of GHG emissions, in alignment with IPCC Guidelines for national inventories (IPCC, 2006) as they are biogenic in origin and do not contribute to GWP. The methodology for calculating GHG emissions associated with wastewater treatment is generally based on guidance provided in the IPCC Guidelines for national inventories; however, more specific emission factors for CH_4 and N_2O are used based on site-specific emissions for representative biological treatment processes. A detailed presentation of the calculations used to estimate process GHG emissions is provided in Appendix Section B.2.

2.2.5 LCI Limitations

Some of the main limitations that readers should understand when interpreting the LCI data and findings are as follows:

- **Support personnel requirements.** Support personnel requirements are excluded from the LCA model. The energy and wastes associated with research and development, sales, administrative personnel, or related activities are not included, as energy requirements and related emissions are assumed to be quite small for support personnel activities.
- **Representativeness of background data.** Background processes are representative of either U.S. average data (in the case of data from the Federal LCA Commons) or European or global average (in the case of Ecoinvent) data. In some cases, European Ecoinvent processes were used to represent U.S. inputs to the model (e.g., for chemical inputs) due to lack of available representative U.S. processes for these inputs. The background data, however, met the criteria listed in the project QAPP for completeness, representativeness, accuracy, and reliability. The overall data quality results for the LCI are provided in Appendix D.
- **Full LCI model data accuracy and uncertainty.** In a complex study with thousands of numeric entries, the accuracy of the data and how it affects conclusions is a difficult subject. The reader should keep in mind the uncertainty associated with LCI data when interpreting the results. Comparative conclusions should not be drawn based on small differences in impact results.
- **Transferability of results.** The LCI data presented here are specific to the PR WWTP. LCI results may vary substantially for other case-specific operating conditions and facilities.

2.3 Life Cycle Impact Assessment Model

The model used to conduct the Life Cycle Impact Assessment was constructed in openLCA version 1.10.3, an open-source LCA software package developed by GreenDelta (GreenDelta, 2020). This open-source format allowed project team members to seamlessly share the LCA model.

Appendix B presents LCI data originally developed in Excel and transferred into the OpenLCA model. Tables in Appendix B present LCI data according to the treatment processes included in the LCA model, noting which processes are relevant for each treatment configuration. LCI flow labels correspond to the “background input” names in Table 2-4.

Interpretation of LCIA results requires understanding the uncertainty associated with inventory data. A Monte Carlo approach was used to estimate uncertainty ranges for the baseline results presented in Section 3. The model was parameterized in OpenLCA to allow uncertainty data attached to each parameter to propagate through the model. Results uncertainty associated with impact assessment was not included in the analysis and is expected to affect the treatment configurations similarly, as the drivers of impact are common across scenarios (See Section 3 for more detail).

A Monte Carlo analysis randomly samples the constructed LCA model based on uncertainty data attached to global parameters, process parameters, and inventory flows. By carrying out this sampling procedure over a large number of model runs (1,000 in this analysis), OpenLCA constructs a histogram of model results (Clavreul et al., 2012). The 5th and 95th percentile values from these model runs were used to establish uncertainty bounds around the Monte Carlo mean. Lognormal distributions were typically used to represent emissions to nature. The lognormal distribution is the default distribution used to model environmental flows in the Ecoinvent 2 database (Ciroth et al., 2012). Triangular distributions are used to define uncertainty for material, energy, and chemical inputs and outputs using minimum, mean, and maximum identified values to define the distribution vertices. Appendix B.1 documents inventory values, associated uncertainty data, supporting assumptions, and sources.

At the analysis level, it is important to consider that uncertainty in inventory or characterization is not purely multiplicative when considering differences between systems (Hong et al., 2010). For many LCA analyses, many background and some foreground processes will be shared between systems. For example, background electricity generation is often shared, and chemical additives or concrete could be shared foreground processes for wastewater treatment. Such shared processes allow for fewer confounding factors when comparing results.

Once all necessary data were input into the openLCA software and reviewed, a system model was created for the parameterized treatment configuration. The models were reviewed to ensure that each elementary flow (e.g., environmental emissions, consumption of natural resources, energy demand) was characterized under each impact category for which a characterization factor was available. LCIA results were then calculated by generating a contribution analysis for the product system based on the defined functional unit of treatment of one-cubic meter of wastewater. Appendix A discusses the detailed LCIA methods used to translate the LCI model in openLCA into the impact results assessed in this study.

ERG compiled LCI data in a central Excel spreadsheet and included a data quality index (DQI) matrix to evaluate the quality of the LCI data. A DQI matrix evaluates data based on five criteria: source reliability, completeness, temporal correlation, geographical correlation, and technological correlation. ERG adhered to EPA guidance for assessing LCI data quality when scoring the DQI (Edelen and Ingwersen, 2016). The results of this evaluation indicate LCI data quality is sufficient for use. A DQI matrix for LCI data can be found in Appendix D.

2.3.1 LCIA Limitations

While limitations of the LCI model are specifically discussed in Section 2.2.5, some of the main limitations that readers should understand when interpreting the LCIA findings are as follows:

- **Transferability of results.** While this study is intended to inform decision-making for a wide range of stakeholders, the impacts presented here relate to a specific WWTP in Santa Fe, New Mexico.
- **Site specificity.** Although the study refers to a specific WWTP, some metrics are not able to provide site-specific results. For example, eutrophication potential, particularly with respect to direct effluent emissions, only captures a direct relationship between potentially eutrophying pollutants that is based on the Redfield ratio (see Appendix A.1 for method description) and does not describe local water quality dynamics.
- **LCIA method uncertainty.** In addition to the uncertainty of the LCI data, there is uncertainty associated with applying LCIA methodologies and normalization factors to aggregated LCI data. For example, two systems may release the same total amount of the same substance, but one quantity may represent a single high-concentration release to a stressed environment while the other quantity may represent the aggregate of many small dilute releases to environments that are well below threshold limits for the released substance. The actual impacts would likely be very different for these two scenarios, but the LCI does not track the temporal and spatial resolution or concentrations of releases in sufficient detail for the LCIA methodology to model the aggregated emission quantities differently. Therefore, it is not possible to state with complete certainty that differences in potential impacts for two systems are significant differences. Although there is uncertainty associated with LCIA methodologies, all LCIA methodologies are applied to different wastewater treatment configurations uniformly. Therefore, comparative results can be determined with a greater confidence than absolute results for one system.

3. LIFE CYCLE IMPACT BASELINE RESULTS

An overview of LCIA results are provided in Figure 3-1. For each metric, results have been standardized by dividing each result by the maximum absolute value across all scenarios so that each can be expressed on a scale of -1 to 1. A value of 1 represents the scenario with the largest impact within a category, and -1 represents the smallest impact. No weighting factors are applied, which implicitly gives equal weight to each of the 13 metrics. Figure 3-1 shows that Scenario 3 (RO) results in the largest impacts across all metrics except eutrophication potential. The remainder of this section illustrates and discusses these results in greater detail.

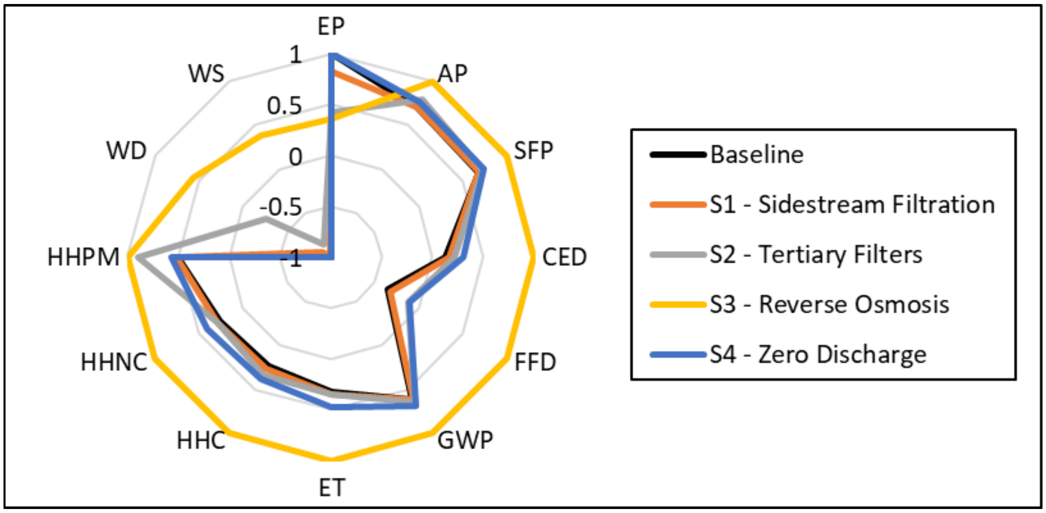

Figure 3-1. Summary of baseline LCIA results for the Baseline Scenario and Scenarios 1–4 (S1–S4). For each metric, results were standardized by dividing each result by the maximum absolute value across all scenarios so that each metric can be expressed on a scale of -1 to 1, where 1 indicates the greatest impact among all scenarios. Metric abbreviations are provided in Table 1-3.

In the following sections, baseline LCIA results are presented in greater detail in four groups based on whether the results pertain broadly to 1) environmental quality, 2) energy and climate, 3) water, or 4) toxicity. For all metrics, impact contributions are presented according to treatment processes or major drivers. Refer to Appendix A for more information on individual impact categories, their underlying environmental issue, and the pollutants that contribute to each impact. A description of treatment processes and major drivers is provided in Table 3-1 and applies to Figure 3-2 through Figure 3-14.

Table 3-1. Description of Impact Contribution Categories.

Category	Description
Processes	
Main Plant—Energy Use	Includes electricity and diesel fuel consumption that cannot be allocated to individual unit processes (due to a lack of meter data).
Primary and Secondary Treatment	Includes landfill disposal of screenings/grit and process air emissions from the biological treatment system.[a]

Post-Secondary Treatment	Process grouping includes disk filtration,[a] ultraviolet disinfection,[a] and tertiary treatment processes for scenarios 1–3.
Biogas Cleaning and Combustion	Process grouping includes biogas cleaning and combustion in the combined heat and power (CHP) system, boiler, or flare.
Sludge Processing and Disposal	Process grouping includes dissolved air flotation,[a] belt filter press,[a] anaerobic digestion,[a] digestate composting, digestate landfilling, and compost land application. Includes environmental credits associated with avoided energy and fertilizer.
Brine Injection	Includes energy and water consumption associated with reverse osmosis brine deep well injection.
Effluent Reuse	Includes energy and avoided energy consumption and emissions to water associated with wastewater effluent reuse.
Effluent Diversion	Includes energy and infrastructure inputs required for effluent diversion to the Rio Grande. All effluent emissions are reflected in the "Effluent Release" process group.
Effluent Release	Includes emissions to surface water from treated wastewater effluent.
Drivers	
WWTP Process Emissions	Direct greenhouse gas emissions from the secondary biological treatment process and anaerobic digesters.
Energy	Net consumption of electricity, diesel, and natural gas at the PR WWTP. Avoided heat and electricity are included in this category and reduce net impact attributed to energy consumption.
Transport	Includes the share of diesel combustion impacts allocated to vehicle use.
Chemicals	Includes all chemicals used at the PR WWTP.
Landfill	Includes all impacts associated with landfilling of digestate and subsequent leachate treatment.
Biogas Combustion	Driver grouping includes biogas cleaning and combustion in the CHP system, boiler, or flare.
Composting	Includes energy and emissions to air associated with digestate composting.
Water Reuse	Includes energy and avoided energy consumption and emissions to water associated with wastewater effluent reuse.
Effluent Diversion	Includes energy and infrastructure inputs required for effluent diversion to the Rio Grande. All effluent emissions are reflected in the "Effluent Release" process group.
Effluent Release	Includes emissions to surface water from treated wastewater effluent.
Land Application	Includes emissions to air and water associated with compost land application.
Avoided Product	Includes avoided fertilizer production. Avoided energy products are included in the "Energy" driver grouping.
Materials	Includes all consumable infrastructure materials modeled for the tertiary treatment processes and diversion pipeline.

[a] Energy consumption is reflected in "Main Plant—Energy Use."

In Sections 3.1 through 3.4, panel "a" in each figure presents net environmental impact results according to treatment process, as well as two sets of uncertainty ranges developed using Monte Carlo analysis. Each set of uncertainty bars was developed based on the 5th and 95th percentile values that result from 1,000 iterations of the LCA model. In cases where negative impacts occur, the total net impact, as well as the uncertainty ranges about the total net impact, may be wholly within the columns in the figures below. The black set of uncertainty bars includes uncertainty estimates associated with all processes in the treatment system (see Table

2-1 for a list of processes in each scenario). These uncertainty ranges include uncertainty that is unique to each scenario, as well as uncertainty estimates for processes that are common to all assessed treatment scenarios (termed "shared uncertainty"). When uncertainty is associated with processes that are common to all treatment systems, it has bearing on the absolute magnitude of impact realized by each treatment system but cannot be used to differentiate between treatment scenario environmental performance.

The blue set of uncertainty bars includes uncertainty estimates associated only with treatment processes that are unique to individual treatment scenarios (e.g., sidestream filtration, MF/RO) or processes in which treatment performance varies according to scenario (e.g., effluent release, effluent reuse). The portion of analysis uncertainty unique to each treatment scenario affects both the absolute magnitude of impact that is potentially realized by each scenario and provides an opportunity to differentiate between scenarios based on independent sources of uncertainty. In situations where blue uncertainty bars do not overlap (even if black bars do), we can be more confident that the mean impacts of each alternative are different.

3.1 Environment

3.1.1 Eutrophication Potential

Figure 3-2 presents eutrophication potential results by treatment process (a) and major drivers (b). Figures a and b both show that effluent release is the predominant contributor to eutrophication potential. Land application of compost is the second largest contributor to eutrophication for all scenarios but contributes a larger relative share of impact for Scenarios 2 and 3, as the contribution from direct effluent release is smaller for those scenarios.

The uncertainty bounds in Figure 3-2 indicate that Tertiary Filtration and Reverse Osmosis (Scenarios 2 and 3) have similar eutrophication impacts and are likely to yield reduced impacts relative to the Baseline Scenario, Sidestream Filtration (Scenario 1), and Zero Discharge (Scenario 4) across the range of conditions described in Appendix B. The largest reduction in eutrophication potential, relative to the Baseline Scenario impact, is achieved in the RO scenario (Scenario 3). Impact uncertainty ranges, particularly the upper bounds, are mostly due to the range of effluent pollutant concentrations illustrated in Table 2-2, and are driven by sources of uncertainty that are unique to each treatment scenario.

As noted in Section 2.2.3.3, nutrient emissions that contribute to eutrophication potential during land application are expected to be similar in magnitude to emissions that would occur in an alternate scenario where chemical fertilizer is used instead of compost. Given this, the eutrophication potential associated with compost land application could reasonably be allocated to the agricultural production system, reducing the net eutrophication potential of all scenarios, thereby eliminating the contribution from land application in panel "b".

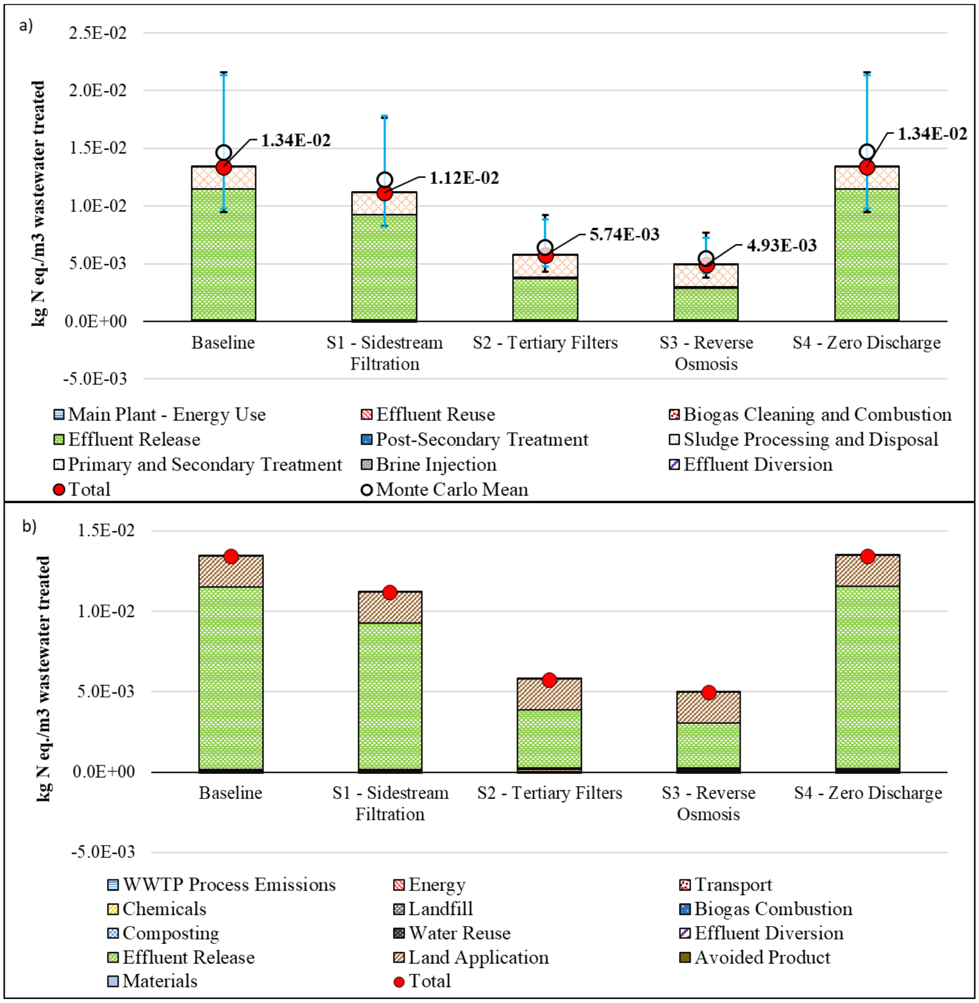

Figure 3-2. Eutrophication potential results for each treatment scenario, including uncertainty ranges as the 5th and 95th percentile results from Monte Carlo simulations. Black uncertainty bars represent combined uncertainty estimates for both shared and unique LCI data for each scenario, and blue bars include uncertainty estimates only for the LCI inputs that are unique to individual scenarios. Non-overlapping areas of the two uncertainty bars indicate uncertainty that is shared across scenarios. Panels a and b show results aggregated according to the different categorizations described in Table 3-1.

LCIA methods are capable of capturing regional differences in potential impact. But they do not model watersheds in enough detail to distinguish potential or actual impact associated with emission of the same quantity of nutrients in either the Rio Grande or Santa Fe Rivers, which leads to the identical potential impacts shown in Figure 3-2 for the Baseline Scenario and Scenario 4. As detailed in Appendix A.1, TRACI eutrophication potential characterization factors are intended to capture the relative influence that each pollutant (nutrients and COD) could have on algae growth in the photic zone of an aquatic ecosystem when released to an environment where it is the limiting nutrient (Norris, 2002). Pollutants in effluent release that are captured in Figure 3-2 include COD, nitrate, ammonia, organic nitrogen, and phosphorus. The influence of additional factors on eutrophication potential, including bioavailability of organic nitrogen and receiving environments, is discussed further in a eutrophication potential sensitivity analysis in Section 4.2.

To provide additional context for the trends illustrated in Figure 3-2 from direct effluent release, Table 3-2 summarizes characterization factors and average annual mass discharges of the major nutrient forms that contribute to the eutrophication potential of direct effluent discharges. Average annual mass discharges are also illustrated in Figure 3-3.

Table 3-2. Summary of average annual COD and nutrient discharges across treatment scenarios.

Pollutant	Charact. Factor (kg N eq./kg pollutant)	Baseline	S1 - Sidestream Filtration	S2 - Tertiary Filtration	S3 - Reverse Osmosis	S4 - Zero Discharge
	Average kg/yr Discharged					
COD	0.05	201,171	201,171	134,114	134,114	201,171
Nitrate (created)	0.24	10,059	10,059	3,353	3,353	10,059
Ammonia	0.78	671	671	671	671	671
Nitrogen, organic	0.99	16,764	16,764	16,764	10,059	16,764
Phosphorus	7.30	6,706	4,694	335	335	6,706

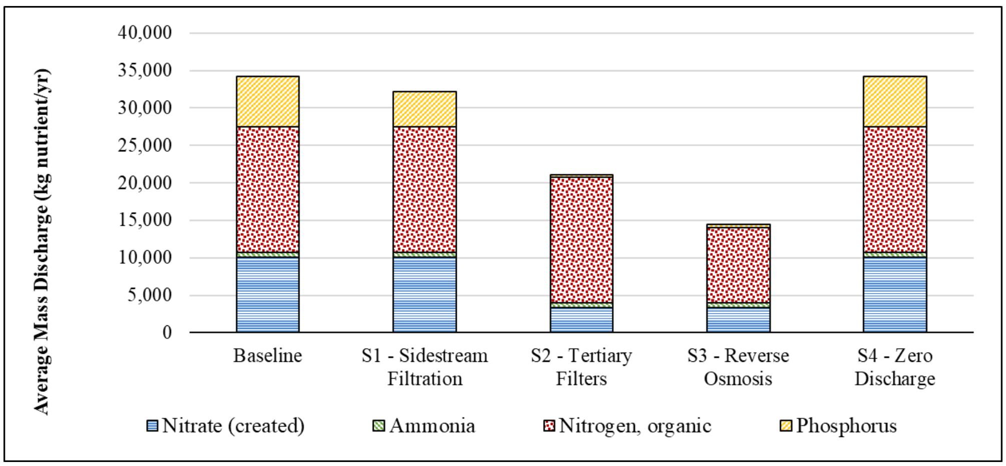

Figure 3-3. Summary of annual nutrient mass discharges across treatment scenarios. COD not shown to not overwhelm nutrient visibility.

3.1.2 Acidification Potential

Figure 3-4 presents acidification potential results by treatment process (a) and major driver (b). The figures reveal that biogas combustion, energy consumption (primarily electricity), and process emissions from digestate composting contribute considerable shares of acidification impact. Biogas combustion releases NO_x and SO_2 emissions that contribute to acidification potential. As illustrated in Figure 3-4, panel b shows a reduced contribution from energy, compared to main plant energy use in panel a, because that category shows the net effect when considering both plant energy consumption and avoided energy produced by the CHP system.

Chemical use contributes moderately to net impact in Scenario 2, increasing the mean impact relative to the Baseline, Scenario 1, and Scenario 4. RO has the highest mean acidification potential due primarily to increased electricity demand from RO operation and deep well injection.

The uncertainty bars in panel a show considerable overlap across the five scenarios, which is almost completely dominated by sources of uncertainty that are common to all treatment scenarios (i.e., blue bars are barely visible). For example, the compost process is the same across all scenarios. While this uncertainty does affect the magnitude of acidification potential within the demonstrated range, it is not independent across scenarios and therefore does not minimize the difference in mean impact. This finding gives greater confidence that differences in mean impact consequentially differentiate treatment scenarios. Parameter uncertainty results, presented in Appendix F, indicate that results are most sensitive to facility energy consumption and compost emissions. The fact that the mean impact for Scenario 3 is at or near the upper bound of the uncertainty range for Baseline, Scenario 1, and Scenario 4 gives reasonable confidence that the RO treatment scenario would lead to increased acidification potential.

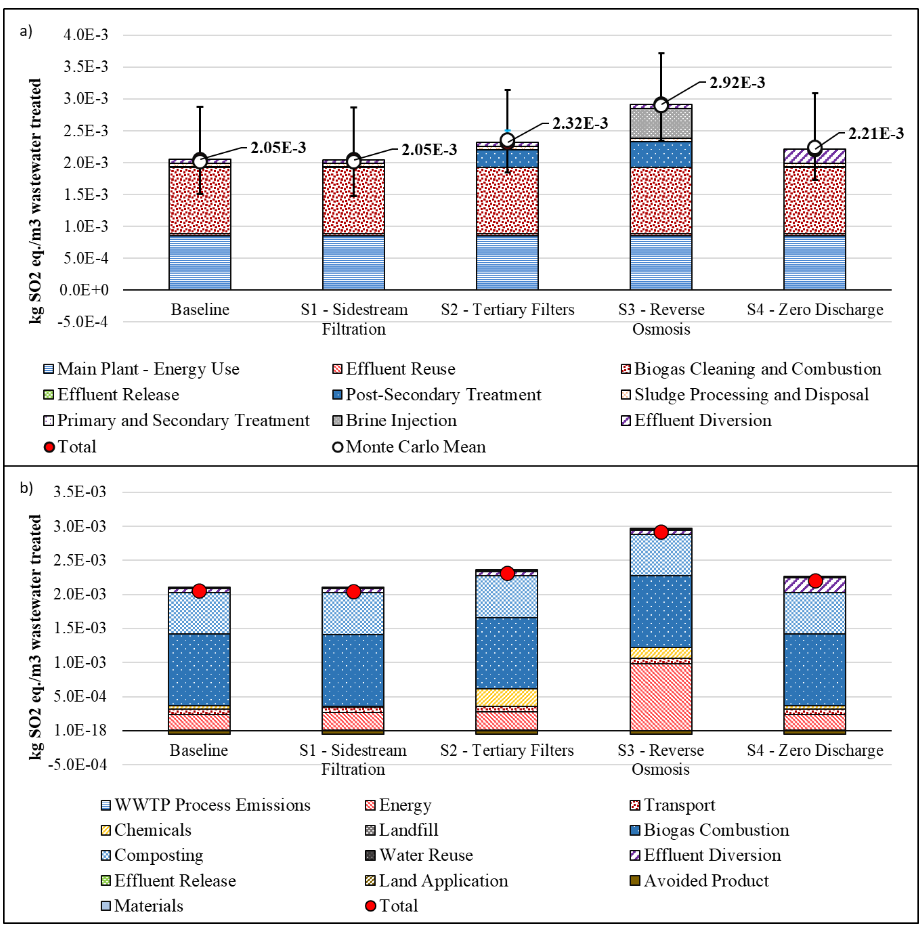

Figure 3-4. Acidification potential results for each treatment scenario, including uncertainty ranges as the 5th and 95th percentile results from Monte Carlo simulations. Black uncertainty bars represent combined uncertainty estimates for both shared and unique LCI data for

each scenario, and blue bars include uncertainty estimates only for the LCI inputs that are unique to individual scenarios. Non-overlapping areas of the two uncertainty bars indicate uncertainty that is shared across scenarios. Panels a and b show results aggregated according to the different categorizations described in Table 3-1.

3.1.3 Smog Formation Potential

Figure 3-5 presents smog formation potential results by treatment process (a) and major driver (b). Biogas combustion and grid electricity consumption are the primary drivers of smog formation impact. As illustrated in Figure 3-5, avoided energy products, which are included in the "sludge processing and disposal" treatment group in panel a, generate a considerable avoided burden credit that reduces the net smog formation potential of all treatment configurations. Chemical production and transportation contribute minorly to impact in this category.

Mean estimates of smog formation are similar for the Baseline, Scenario 1, Scenario 2, and Scenario 4, with nearly complete overlap of both uncertainty ranges. The lower bound of the combined uncertainty range for Scenario 3 is at or near the upper bound of uncertainty estimates for the other treatment options, giving high confidence that the RO treatment option will lead to a significant increase in smog formation impact.

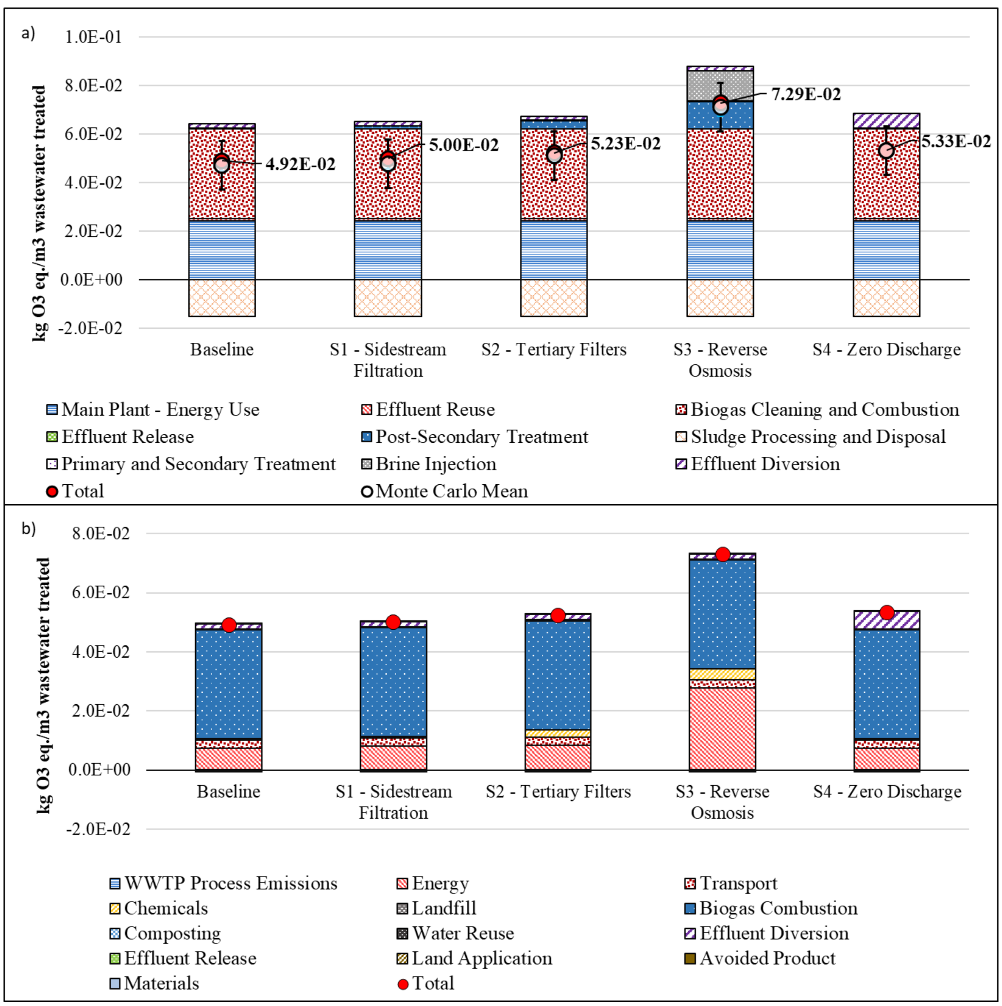

Figure 3-5. Smog formation potential results for each treatment scenario, including uncertainty ranges as the 5th and 95th percentile results from Monte Carlo simulations. Black uncertainty bars represent combined uncertainty estimates for both shared and unique LCI data for each scenario, and blue bars include uncertainty estimates only for the LCI inputs that are unique to individual scenarios. Non-overlapping areas of the two uncertainty bars indicate uncertainty that is shared across scenarios. Panels a and b show results aggregated according to the different categorizations described in Table 3-1.

3.2 Energy and Climate

3.2.1 Cumulative Energy Demand

Figure 3-6 presents cumulative energy demand (CED) results by treatment process (a) and major driver (b). The avoided energy credits associated with anaerobic digestion, which are included in the "sludge processing and disposal" treatment group in panel a, considerably reduce the net CED of all treatment systems, leading to a small net positive energy demand for the Baseline and Scenario 1. Combined uncertainty ranges for these scenarios show the potential to achieve a net zero energy demand. The CEDs of Scenario 1 and Scenario 2 are similar to the Baseline scenario, with the minor CED increases in Scenario 2 being attributable to alum production. The unique uncertainty range for Scenario 4 has no overlap with the Baseline, Scenario 1, or Scenario 2, indicating a consequential increase in CED attributable to the energy demand of effluent diversion. The CED of Scenario 3 is significantly greater than that of the other scenarios due to the energy intensity of RO and brine deep well injection. As biogas enters the treatment plant as a waste product, the energy content of the wastewater and the resulting biogas is excluded from CED estimates.

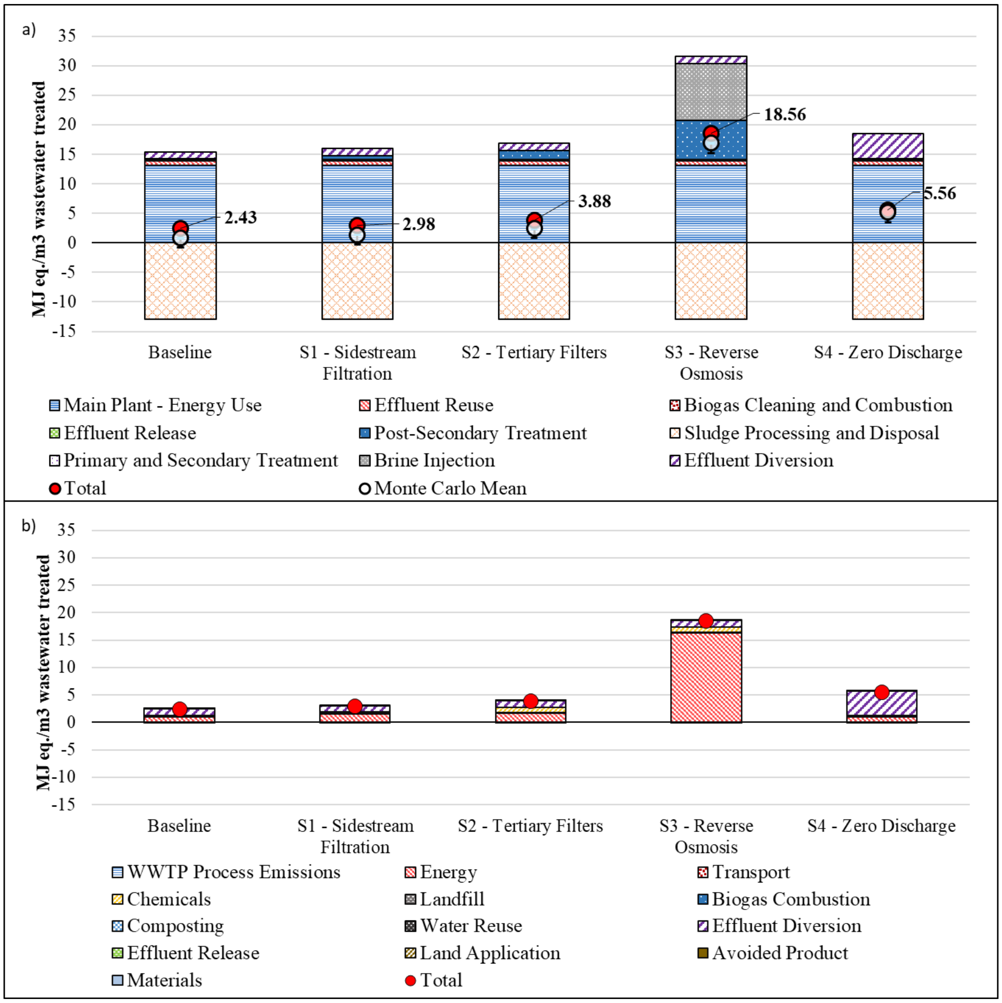

Figure 3-6. Cumulative energy demand results for each treatment scenario, including uncertainty ranges as the 5th and 95th percentile results from Monte Carlo simulations. Black uncertainty bars represent combined uncertainty estimates for both shared and unique LCI data for each scenario, and blue bars include uncertainty estimates only for the LCI inputs that are unique to individual scenarios. Non-overlapping areas of the two uncertainty bars indicate uncertainty that is shared across scenarios. Panels a and b show results aggregated according to the different categorizations described in Table 3-1.

3.2.2 Fossil Fuel Depletion

Figure 3-7 presents fossil fuel depletion results by treatment process (a) and major driver (b). Trends are similar to those discussed for CED with slightly more pronounced benefits for the avoided products that result from sludge processing and disposal, which include energy and fertilizer. The reduced impact associated with avoided products leads to net benefits for the Baseline, Scenario 1, Scenario 2, and Scenario 4. Chemical use contributes moderately to impact in Scenario 2 and Scenario 3. Energy demand associated with effluent diversion also contributes moderately to fossil fuel depletion in Scenario 4. Avoided fertilizer production provides a minor, but non-negligible, reduction in net fossil fuel depletion. As with CED, there is minimal uncertainty associated with the fossil fuel depletion results, and Scenario 3 demonstrates significantly greater impact than the other four scenarios.

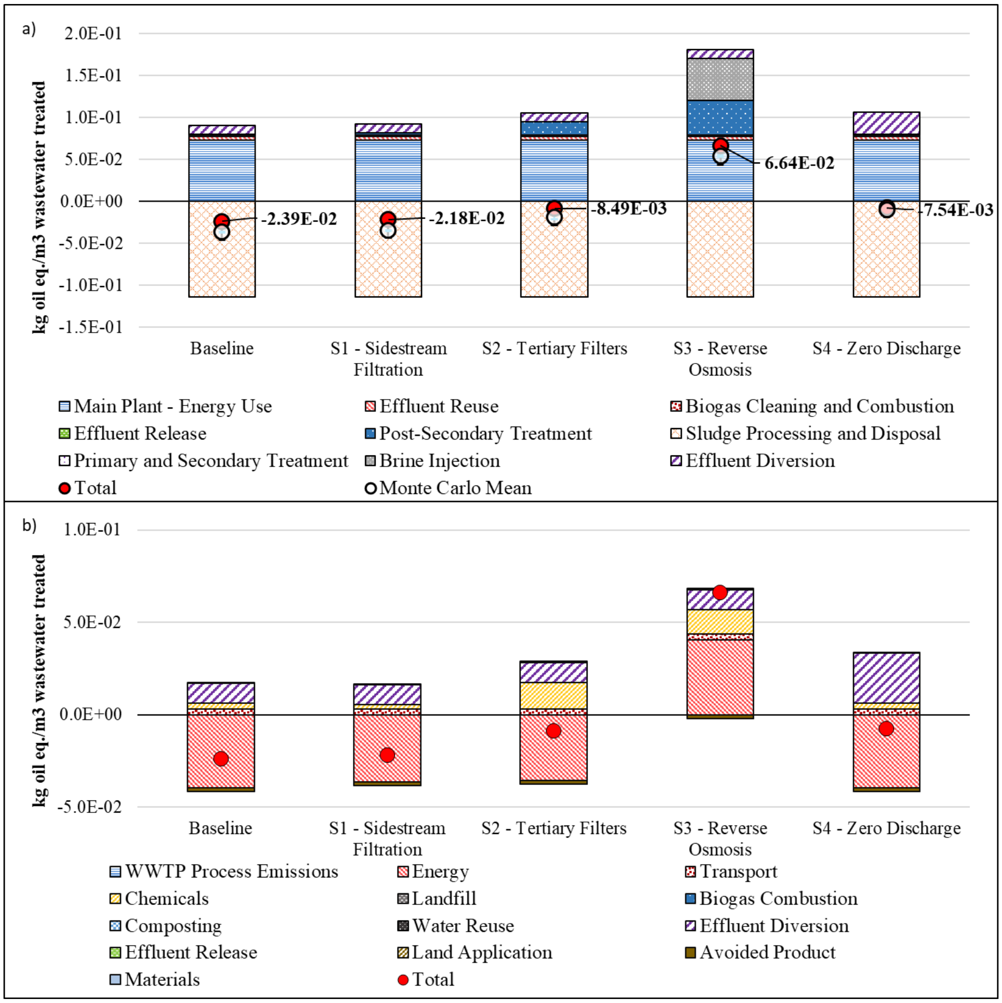

Figure 3-7. Fossil fuel depletion results for each treatment scenario, including uncertainty ranges as the 5th and 95th percentile results from Monte Carlo simulations. Black uncertainty bars represent combined uncertainty estimates for both shared and unique LCI data for each scenario, and blue bars include uncertainty estimates only for the LCI inputs that are unique to individual scenarios. Non-overlapping areas of the two uncertainty bars indicate uncertainty that is shared across scenarios. Panels a and b show results aggregated according to the different categorizations described in Table 3-1.

3.2.3 Global Warming Potential

Figure 3-8 presents GWP results by treatment process (a) and major driver (b). Process GHG emissions from secondary treatment and main plant electricity demand are the largest contributors to GWP impact (panel a). Sludge processing and disposal registers a net reduction in GWP, but the effect is muted compared to other impact categories such as CED and fossil fuel depletion, as process GHG emissions from anaerobic digestion, composting, and land application counteract the benefit of avoided fertilizer and energy products. Digestate landfilling contributes moderately to gross impact (panel b) for all treatment scenarios.

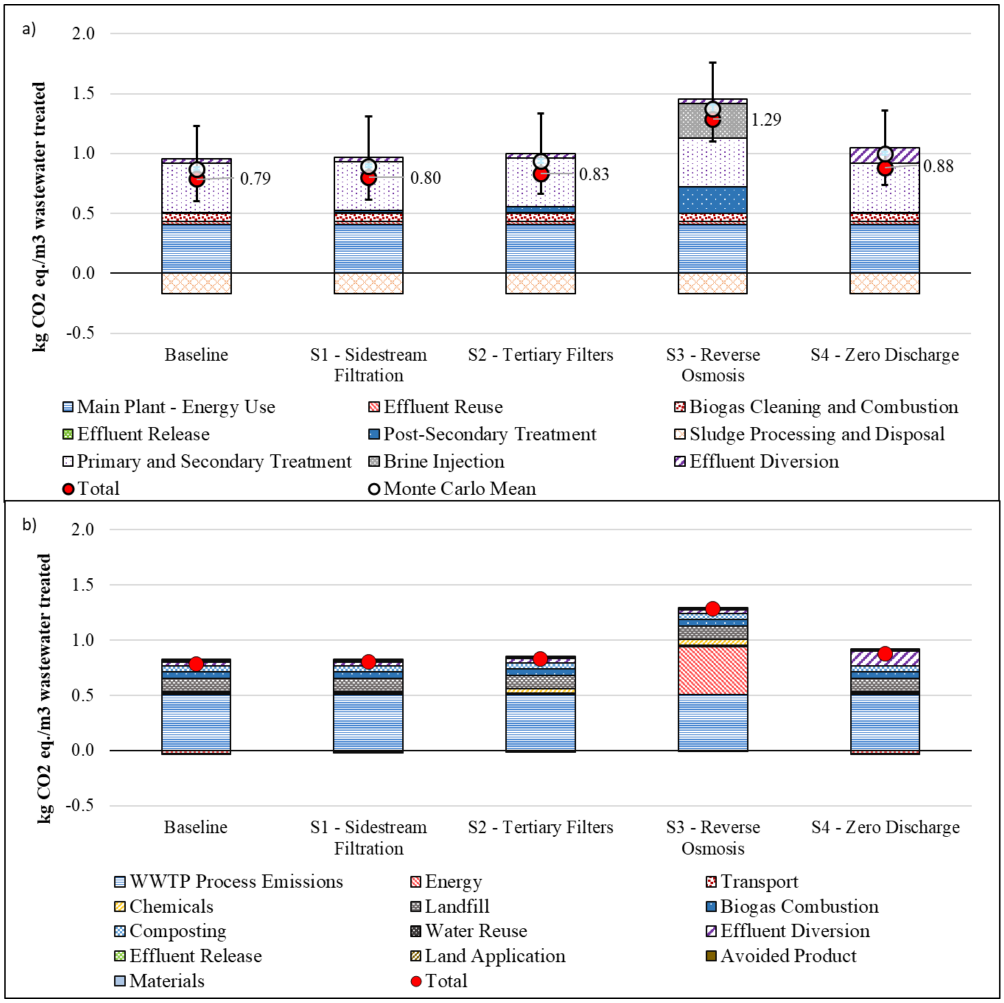

Figure 3-8. Global warming potential results for each treatment scenario, including uncertainty ranges as the 5th and 95th percentile results from Monte Carlo simulations. Black uncertainty bars represent combined uncertainty estimates for both shared and unique LCI data for each scenario, and blue bars include uncertainty estimates only for the LCI inputs that are unique to individual scenarios. Non-overlapping areas of the two uncertainty bars indicate uncertainty that is shared across scenarios. Panels a and b show results aggregated according to the different categorizations described in Table 3-1.

Most of the uncertainty in GWP impact is associated with treatment processes that are shared across scenarios, giving greater confidence that true differences in mean impact exist across scenarios. However, the unique uncertainty ranges overlap for the Baseline and Scenario 1, indicating that there is no meaningful difference in GWP between these scenarios. The Monte Carlo mean for Scenario 3 is 37% greater than the Monte Carlo mean of the next most impactful scenario (Scenario 4), giving high confidence that the RO treatment scenario would lead to a considerable increase in GWP relative to the other treatment options. The uncertainty ranges are skewed towards greater impact, pulling the Monte Carlo mean higher than the analysis (best estimate) mean. This skew in the uncertainty results demonstrates the potential for considerably greater impact if management practice encourages process emissions and system performance in the upper end of the uncertainty ranges described in Appendix B.

3.3 Water

3.3.1 Water Depletion

Figure 3-9 presents water depletion results by treatment process (a) and major driver (b). Water depletion refers to consumptive uses of water as described in Appendix A.8. Its unit of cubic meter per cubic meter of wastewater treated (m^3/m^3 wastewater treated) can be interpreted as the cubic meters of water depleted, or consumed, for every cubic meter of water treated. Effluent reuse is one of the main offsets of water depletion and provides a persistent benefit to the wastewater treatment facility regardless of the treatment option pursued. Chemical consumption and upstream production are a moderate or major sources of water depletion for Scenario 1, Scenario 2, and Scenario 3. Production of alum in Scenario 2 uses a considerable quantity of water, rivaling the benefit of effluent reuse and introducing uncertainty into the Scenario 2 water depletion results.

The uncertainty depicted in this figure is predominantly due to the contribution of alum and uncertainty in how much of it is needed to reduce effluent phosphorus concentrations. The amount of phosphorus that will need to be removed in the tertiary filters depends on the performance of the secondary biological process. The Scenario 2 unique uncertainty range overlaps with the mean water depletion estimate for the RO treatment scenario. While the realization of this situation is possible, it is not expected under average operating conditions if the biological treatment system is performing according to design standards.

Deep well injection of RO brine removes nearly 30% of wastewater treated by RO from active circulation in the watershed, resulting in depletion of approximately 0.17 m^3/m^3 wastewater treated. Tertiary treatment filters do not process the full quantity of secondary effluent, as described in Section 2.2.2.4. This process has the benefit of sequestering pollutants away from humans and sensitive ecosystems but depletes available water resources. Brine disposal is labeled as WWTP process emissions in panel b.

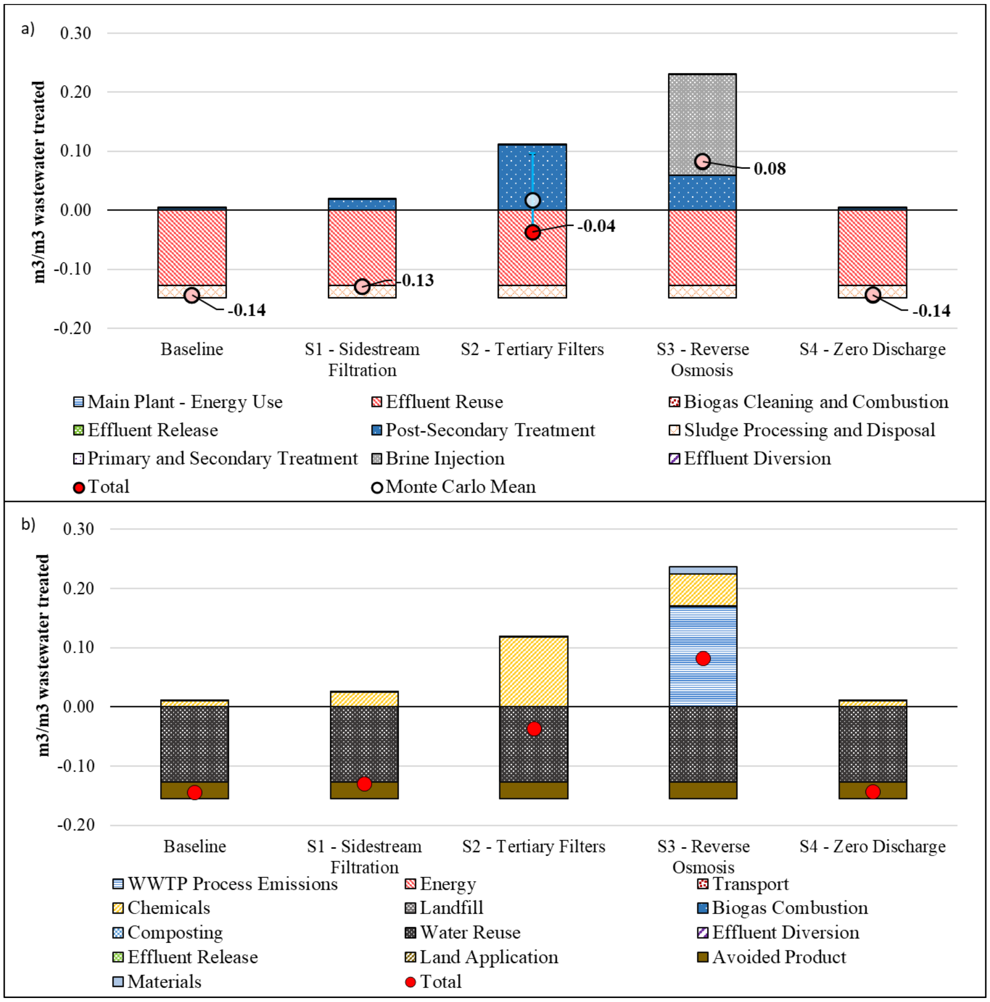

Figure 3-9. Water depletion results for each treatment scenario, including uncertainty ranges as the 5th and 95th percentile results from Monte Carlo simulations. Black uncertainty bars represent combined uncertainty estimates for both shared and unique LCI data for each scenario, and blue bars include uncertainty estimates only for the LCI inputs that are unique to individual scenarios. Non-overlapping areas of the two uncertainty bars indicate uncertainty that is shared across scenarios. Panels a and b show results aggregated according to the different categorizations described in Table 3-1.

3.3.2 Water Scarcity

Figure 3-10 presents water scarcity results by treatment process (a) and major driver (b). Water scarcity builds on water depletion results, where contributions to water depletion are further characterized depending on where that depletion occurs and how scarce water is in that location relative to the rest of the world. Water scarcity characterization factors are on a scale of 0.1 to 100 with units of cubic meter world equivalents per cubic meter (m^3 world equivalents/m^3), representing areas with no water stress (0.1) to areas with very high water stress (100) (Boulay et al., 2018). For example, if 1 cubic meter of water were depleted in Orlando, Florida, where water is less scarce and water scarcity factors generally range from 1–5, its water scarcity impact would be 1–5 m^3 world equivalents/m^3. Conversely, water scarcity factors in

Santa Fe are 100, as water is most scarce there according to the AWARE method (Boulay et al., 2018). Therefore, if 1 cubic meter of water were depleted in Santa Fe, its water scarcity impact would be 100 m^3 world equivalents/m^3. For more information on method development and interpretation, see Appendix Section A.9.

The general trends and drivers of water scarcity are the same as those of water depletion; however, water scarcity results are weighted to highlight the burdens and benefits of water use and reuse in water-scarce regions such as north-central New Mexico. The water scarcity metric highlights the benefits of reusing wastewater effluent in Santa Fe (results in a large offset, or negative value in Figure 3-10, due to the high-water scarcity factor of 100 in Santa Fe), while drawing attention to the issues surrounding brine water disposal (results in a large impact, or positive value in Figure 3-10, again due to the high water scarcity factor of 100 in Santa Fe). Based on the current model, the primary impact of brine water disposal is captured by water scarcity as we assume the brine that is injected (design flow of 2 MGD) sequesters the associated water indefinitely, removing it (and any co-occurring contaminants) from the hydrologic cycle. Water is less scarce nationally than it is in the Santa Fe region, and therefore this water scarcity analysis minimizes the scarcity concerns associated with water use in, for example, chemical production supply chains and electricity production. The net effect, due to brine injection, in Scenario 3 is that loss of brine water leads to a world equivalent loss of 5 m^3 of water per m^3 of treated wastewater, highlighting the importance of this loss in the Santa Fe region.

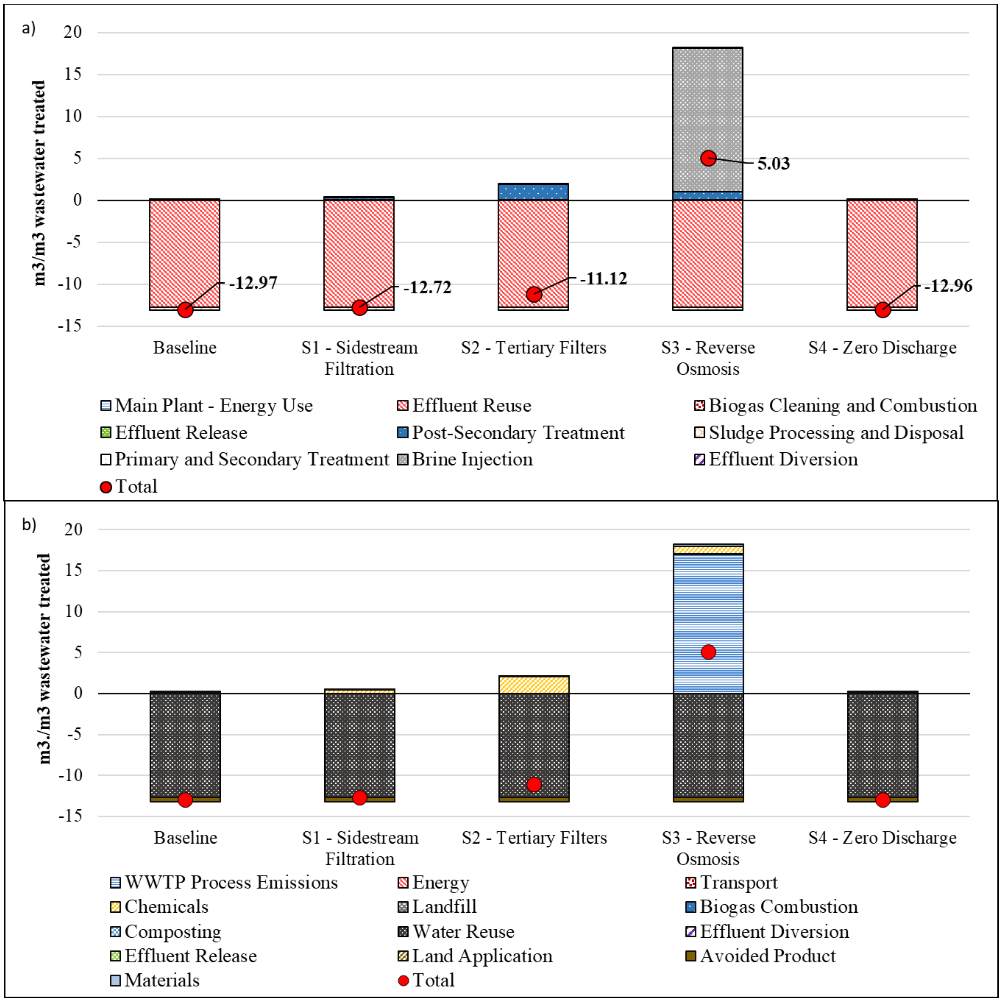

Figure 3-10. Water scarcity results for each treatment scenario. Panels a and b show results aggregated according to the different categorizations described in Table 3-1.

3.4 Toxicity

3.4.1 Ecotoxicity

Figure 3-11 presents ecotoxicity results by treatment process (a) and major driver (b). Electricity consumption and production are the primary drivers of ecotoxicity across all treatment scenarios. Detailed review of model results shows that ecotoxicity of electricity production is dominated by the presence of nuclear energy in the Arizona/New Mexico regional grid mix and release of vanadium during the fuel extraction process. Nuclear energy contributes nearly 19% of the region's fuel resources (Table 2-5).

Effluent release is a minor, but non-negligible, contributor to ecotoxicity impact for the Baseline Scenario, Scenario 1, Scenario 2, and Scenario 4. Zinc is the primary pollutant contributing to ecotoxicity of effluent release. Scenario 3 (RO) nearly eliminates ecotoxicity impacts related to effluent discharge. However, the increased energy demand of the RO treatment scenario significantly increases net ecotoxicity impact relative to the other treatment configurations. Toxicity impacts associated with brine disposal are not included here, as it is assumed deep well injection sequesters brine away from any receiving environment. However, this is a limitation of the current model and should be evaluated in future work.

The increased electricity demand of the full diversion scenario (Scenario 4) contributes to a moderate increase in ecotoxicity impact. This increase is significant enough that it minimizes overlap of uncertainty bounds for Scenario 4 with the Baseline, Scenario 1, and Scenario 2. The latter three scenarios have similar ecotoxicity impacts. Scenario 3 (RO) has the highest ecotoxicity impact across all scenarios.

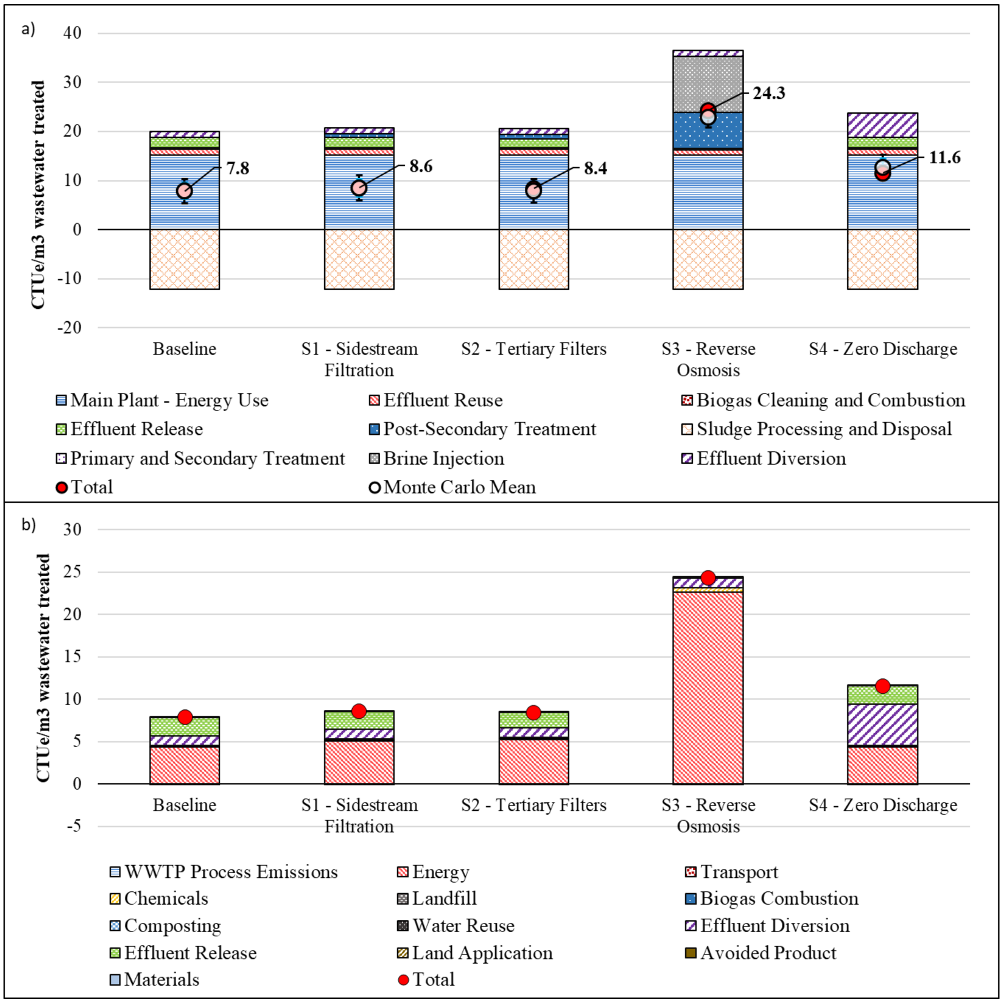

Figure 3-11. Ecotoxicity results for each treatment scenario, including uncertainty ranges as the 5th and 95th percentile results from Monte Carlo simulations. Black uncertainty bars represent combined uncertainty estimates for both shared and unique LCI data for each scenario, and blue bars include uncertainty estimates only for the LCI inputs that are unique to individual scenarios. Non-overlapping areas of the two uncertainty bars indicate uncertainty that is shared across scenarios. Panels a and b show results aggregated according to the different categorizations described in Table 3-1.

3.4.2 Human Health—Particulate Matter Formation

Figure 3-12 presents particulate matter formation potential results by treatment process (a) and major driver (b). Panel a indicates that main plant electricity consumption and post-secondary treatment processes are the main contributors to particulate matter formation. Panel b illustrates that the majority of post-secondary treatment impact comes from chemical consumption. Biogas combustion contributes moderately to particulate matter impact for all treatment scenarios.

Sludge processing and disposal shows a minor net reduction in impact in panel a. The results in panel b demonstrate that composting process emissions are one of the main drivers of particulate matter impact and offset the benefit of avoided energy and fertilizer production. Avoided fertilizer production (labeled avoided product in panel b) yields a larger benefit here than has been demonstrated for other impact categories.

The uncertainty assessment results indicate that most uncertainty is attributable to treatment processes that are common to all scenarios. The upper end of the uncertainty range for Scenario 2 is an exception to that and is attributable to chemical consumption. Given this, the analysis is unable to distinguish the particulate matter formation impact of Scenarios 2 and 3. However, the lower bound of Scenario 3 is higher, giving us greater confidence that the Baseline, Scenario 1, and Scenario 4 will yield reduced impact in this category relative to the RO treatment option.

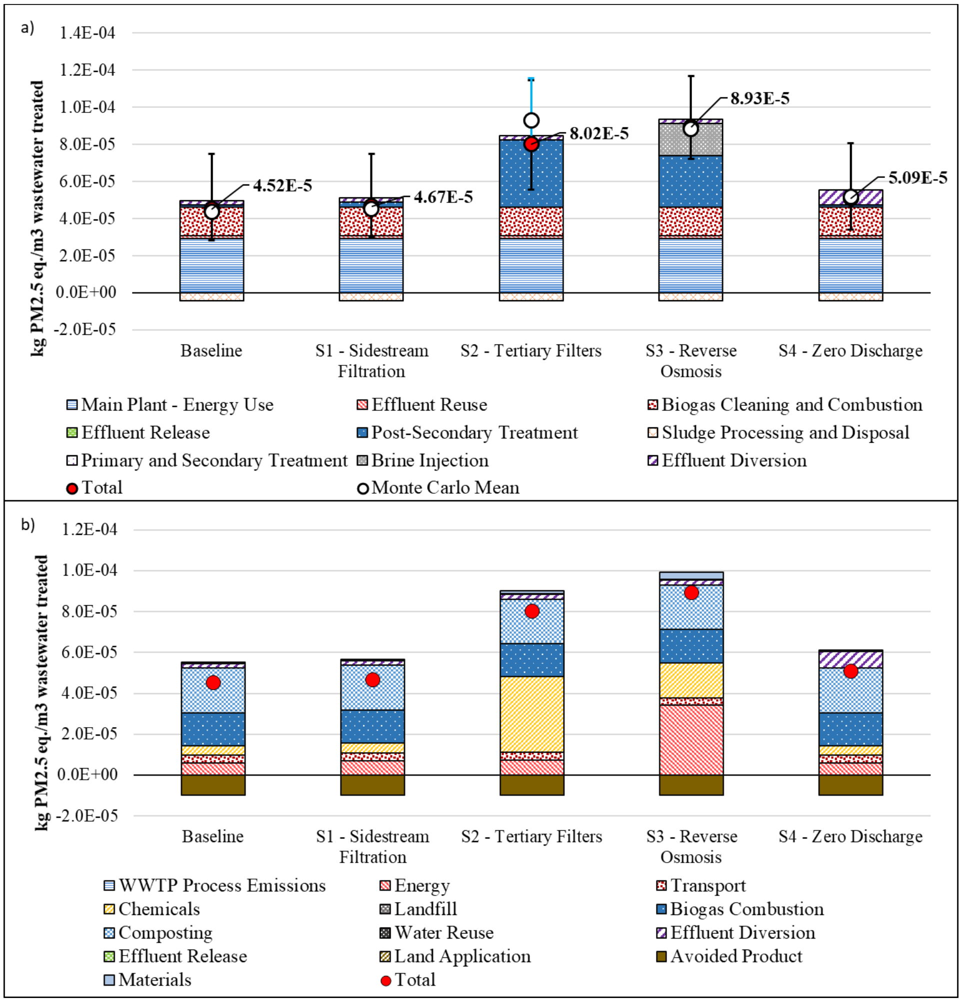

Figure 3-12. Human health—particulate matter formation results for each treatment scenario, including uncertainty ranges as the 5th and 95th percentile results from Monte Carlo simulations. Black uncertainty bars represent combined uncertainty estimates for both shared and unique LCI data for each scenario, and blue bars include uncertainty estimates only for the LCI inputs that are unique to individual scenarios. Non-overlapping areas of the two uncertainty bars indicate uncertainty that is shared across scenarios. Panels a and b show results aggregated according to the different categorizations described in Table 3-1.

3.4.3 Human Health Toxicity—Cancer Potential

Figure 3-13 presents human health toxicity—cancer potential results by treatment process (a) and major driver (b). Taken together, panels a and b demonstrate that electricity consumption is the predominant driver of toxicity cancer impact. With the exception of chemical use in Scenario 2, all of the processes and driver categories depicted in Figure 3-13 are linked to electricity consumption or production. As with ecotoxicity results, the nuclear fuel extraction process contributes most of the impact associated with electricity production. Emissions of arsenic (V), lead, and mercury are responsible for this impact.

While effluent release does not strongly contribute to baseline results, detailed review of the openLCA model reveals that the positively skewed uncertainty range for the Baseline Scenario and Scenarios 1, 2, and 4 is strongly influenced by the outlier metal concentrations in historical water quality data. Triangular distributions are used as a conservative estimate of uncertainty for metal effluent concentrations and lead to uncertainty ranges that skew towards higher values for the non-RO scenarios. Arsenic released to water is the primary pollutant contributing to toxicity cancer potential in the higher end of the uncertainty range. It should be noted that the influence of these outliers would likely be minimal under average operating conditions and is likely enhanced by the Monte Carlo simulation approach. The minimal uncertainty associated with the RO treatment process indicates the effectiveness of this membrane technology in removing pollutants that contribute to human toxicity cancer potential.

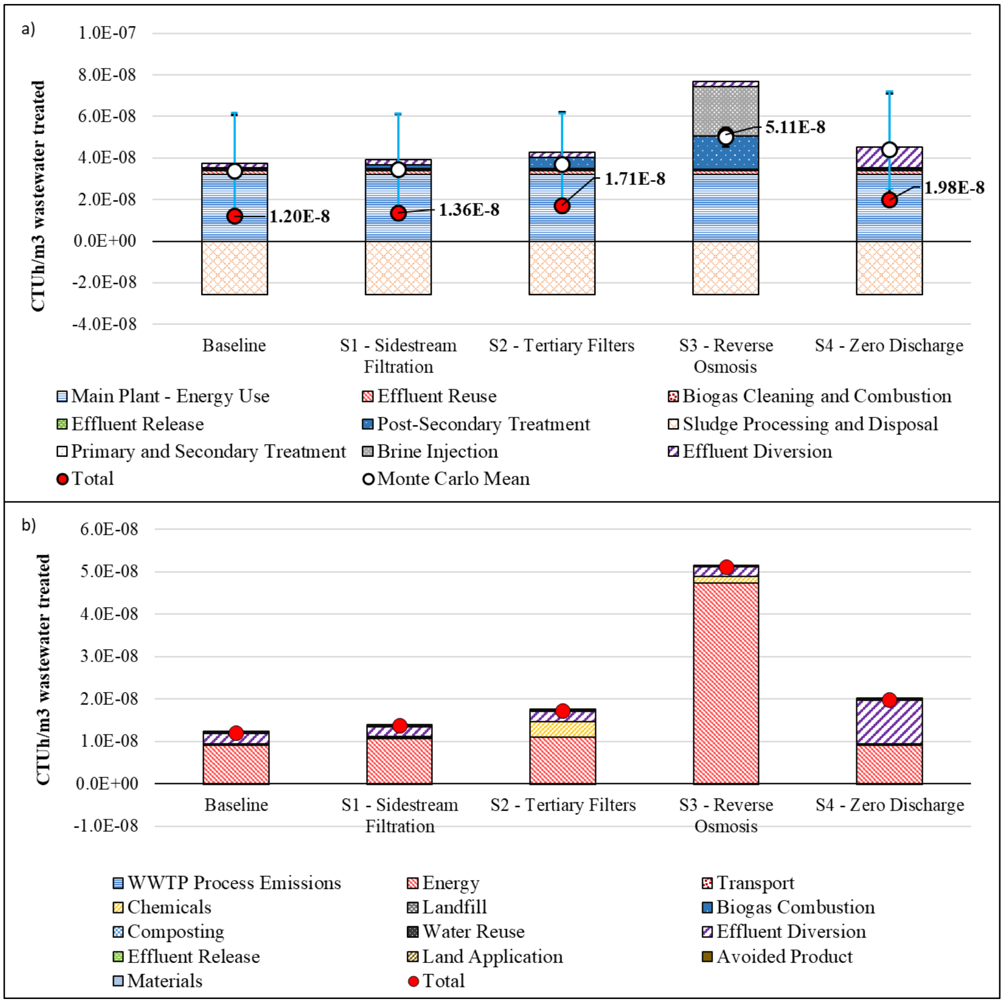

Figure 3-13. Human health toxicity—cancer potential results for each treatment scenario, including uncertainty ranges as the 5th and 95th percentile results from Monte Carlo simulations. Black uncertainty bars represent combined uncertainty estimates for both shared and unique LCI data for each scenario, and blue bars include uncertainty estimates only for the LCI inputs that are unique to individual scenarios. Non-overlapping areas of the two uncertainty bars indicate uncertainty that is shared across scenarios. Panels a and b show results aggregated according to the different categorizations described in Table 3-1.

3.4.4 Human Health Toxicity—Noncancer Potential

Figure 3-14 presents human toxicity—noncancer results by treatment process (a) and major driver (b). Taken together, panels a and b demonstrate that electricity consumption is the predominant driver of toxicity noncancer impact. All the processes and driver categories depicted in Figure 3-14 are linked to electricity consumption or production. Emissions of lead, mercury, and arsenic (V) are responsible for this impact.

As described for human toxicity—cancer, while effluent release does not strongly contribute to baseline results, detailed review of the open LCA model reveals that the positively skewed uncertainty range is strongly influenced by the outlier metal concentrations in historical water quality data. Triangular distributions are used as a conservative estimate of uncertainty for metal effluent concentrations and lead to uncertainty ranges that skew towards higher values for the non-RO scenarios. Arsenic released to water is the primary pollutant contributing to toxicity noncancer potential in the higher end of the uncertainty range It should be noted that the influence of these outliers would likely be minimal under average operating conditions and is likely enhanced by the Monte Carlo simulation approach. The minimal uncertainty associated with the RO treatment process indicates the effectiveness of this membrane technology in removing pollutants that contribute to human toxicity noncancer potential.

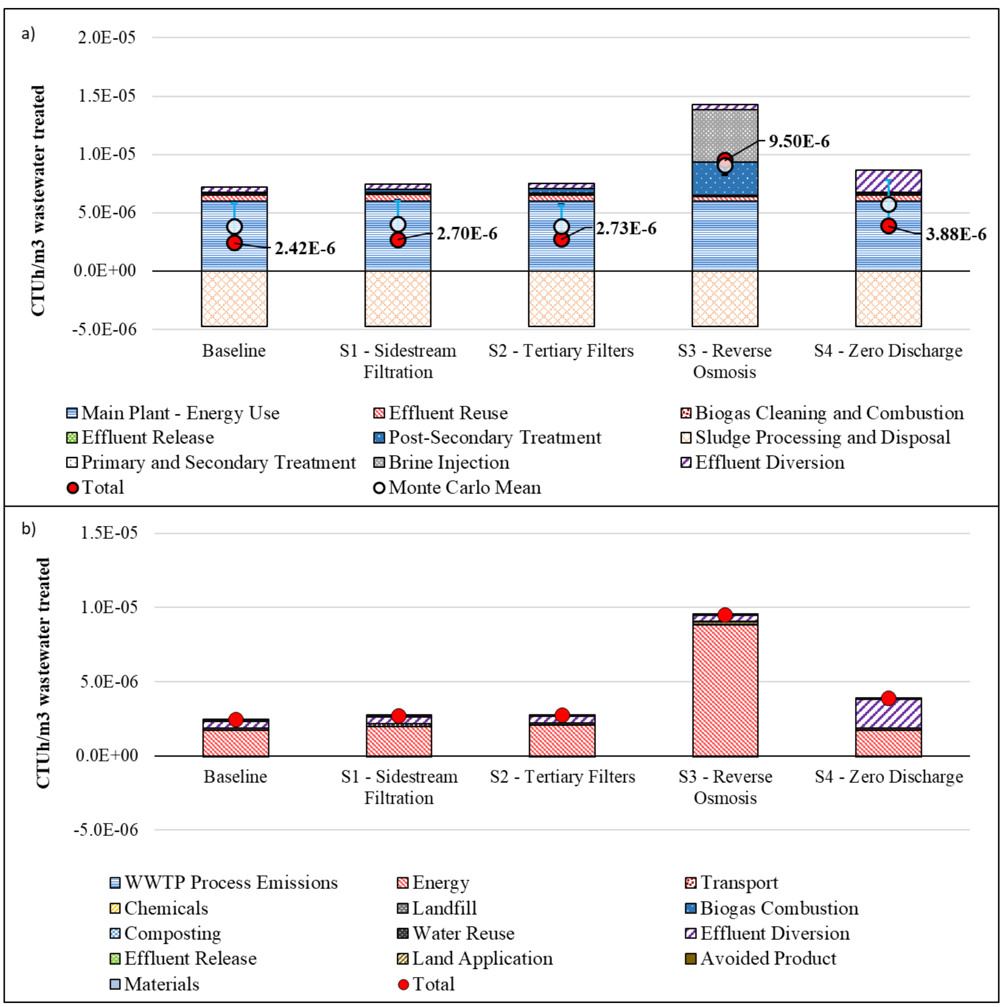

Figure 3-14. Human health toxicity—noncancer potential results for each treatment scenario, including uncertainty ranges as the 5th and 95th percentile results from Monte Carlo simulations. Black uncertainty bars represent combined uncertainty estimates for both shared and unique LCI data for each scenario, and blue bars include uncertainty estimates only for the LCI inputs that are unique to individual scenarios. Non-overlapping areas of the two uncertainty bars indicate uncertainty that is shared across scenarios. Panels a and b show results aggregated according to the different categorizations described in Table 3-1.

3.5 Normalization and Standardization

3.5.1 Standard Normalization

Normalization is an optional step in LCIA that aids in understanding the significance of impact assessment results. Normalization is conducted by dividing the impact category results by a normalization factor. The normalization factor is typically the environmental burdens of the region of interest either on an absolute or per capita basis. The results presented in this study are normalized to reflect impacts on the basis of per person equivalents in the U.S. using TRACI 2.1 normalization factors (Ryberg et al., 2014) and data from the Building Industry Reporting and Design for Sustainability Database (Lippiatt et al., 2013) (Table 3-3). Some impact categories are not included due to lack of available normalization factors.

Table 3-3. U.S. Per Capita Normalization Factors (Lippiatt et al., 2013; Ryberg et al., 2014).

Impact Category	Unit	Normalization Factor (U.S., 2008)	Impact per Person[a]	Source
Eutrophication	kg N eq/yr	6.6E+9	22	Ryberg et al., 2014
Global warming	kg CO_2 eq/yr	7.4E+12	24,334	Ryberg et al., 2014
Acidification	kg SO_2 eq/yr	2.8E+10	92	Ryberg et al., 2014
Smog	kg O_3 eq/yr	4.2E+11	1,381	Ryberg et al., 2014
Particulate Matter Formation	kg $PM_{2.5}$ eq/yr	7.4E+9	24	Ryberg et al., 2014
Water Depletion	L H_2O eq/yr	1.7E+14	559,027	Lippiatt et al., 2013

[a] Impact per person calculated using 2008 U.S. population of 304,100,000 (World Bank, 2017).

By multiplying impact results calculated in this study (impact per m^3) by the annual volume of domestic wastewater treated each year at the PR WWTP (4.85 MGD or 6,705,006 m^3/yr [Section 1.2]), dividing by the service population (85,000 residential customers [Section 1.2]), and dividing by per capita normalization factors, it is possible to calculate the approximate annual contribution of wastewater treatment to the total per capita impact of a Santa Fe resident in each impact category. This calculation excludes impacts from commercial, public, and industrial sources, and therefore overestimates the impact from individuals. The results of this calculation for the five treatment scenarios and environmental impact in six categories are presented in Table 3-4.

Table 3-4. Normalized impact results, expressed as the percent of per capita impacts allocated to wastewater treatment.

Impact Category	Baseline	S1 - Sidestream Filtration	S2 - Tertiary Filters	S3 - Reverse Osmosis	S4 - Zero Discharge
Eutrophication Potential	4.9%	4.1%	2.1%	1.8%	4.9%
Global Warming Potential	0.25%	0.26%	0.27%	0.42%	0.29%
Acidification Potential	0.18%	0.18%	0.20%	0.25%	0.19%
Smog Formation Potential	0.28%	0.29%	0.30%	0.42%	0.30%
Particulate Matter Formation	0.01%	0.02%	0.03%	0.03%	0.02%
Water Depletion	-2.0%	-1.8%	-0.52%	1.2%	-2.0%

Normalized results show that, of the impacts for which normalization factors are available, eutrophication impacts make up the largest contribution to typical per capita impacts, ranging from 2% to 5%. Impacts of GWP, acidification, and smog formation make up less than 1%, ranging from 0.2% to 0.4%. Normalized water depletion results demonstrate the widest variability across treatment scenarios with a minimum normalized impact of -2% for Scenarios 1 and 4, and a maximum normalized impact of 1.2% for Scenario 3. Normalized results show that impacts associated with water depletion are comparable to those of eutrophication for Scenario 3. Water depletion results do not account for local water scarcity, placing further emphasis on the importance of this inventory metric in the Santa Fe region.

The greater proportion of impacts made up by eutrophication is reasonable, as the direct discharge of nutrients and other eutrophying constituents is one of the main components of a WWTP. Similarly, because most of the wastewater is returned to the environment and is not depleted (except for certain unit processes in Scenarios 2 and 3), the relatively small fractions of per capita water depletion identified in these results are reasonable in the context of typical water consumption. For reference, 559,027 liters of water per person per year (Table 3-3) equates to 405 gallons per person per day, which represents both direct use of water (e.g., drinking, bathing) and indirect use associated with production of products and services used by the typical person each day (e.g., agriculture).

3.5.2 Santa Fe GHG Inventory

The City of Santa Fe’s Environmental Services Division analyzed GHG emissions from all sources within city limits following a protocol developed by the Compact of Mayors (City of Santa Fe, 2017). They found the average per capita GHG emissions for a Santa Fe resident to be 10 metric tons per year, compared to a New Mexico state average of 32 metric tons per year and a U.S. average of 17 metric tons per year.

Table 3-5 shows the portion of Santa Fe resident per capita GHG emissions that would be attributed to study treatment scenarios. Contributions range from 0.62% for Baseline and Scenario 1 to 1.0% for Scenario 3. These contributions are higher than normalized results based on TRACI 2.1 normalization factors (Table 3-3), as the City of Santa Fe (2017) estimates per capita GHG emissions of 10 metric tons per year, compared to the 24 metric tons per year national average estimated by Ryberg et al. (2014).

Table 3-5. Summary of treatment scenario GHG emissions, compared to Santa Fe per capita emissions.

Parameter	Baseline	S1 - Side-stream Filtration	S2 - Tertiary Filters	S3 - Reverse Osmosis	S4 - Zero Discharge	Source
Wastewater-Based GHG Emissions, This Study						
kg CO_2 eq./m^3 treated	0.79	0.80	0.83	1.29	0.84	This study
m^3 treated per year	6.71E+06	6.71E+06	6.71E+06	6.71E+06	6.71E+06	This study (4.85 MGD)
kg CO_2 eq./year	5.27E+06	5.37E+06	5.58E+06	8.63E+06	5.65E+06	Calculated
Population served	85,000	85,000	85,000	85,000	85,000	Carollo, 2018
kg CO_2 eq./person/year	62	63	66	102	66	Calculated
Santa Fe GHG Emissions, City of Santa Fe						
kg CO_2 eq./person/year	10,000	10,000	10,000	10,000	10,000	City of Santa Fe, 2017
WWTP fraction	0.62%	0.63%	0.66%	1.02%	0.66%	Calculated

3.5.3 Results Standardized to Nutrient Removal

Generally, model results throughout this study are standardized to the study's functional unit, which is a cubic meter of treated wastewater. In studies such as this, however, standardizing to a different unit of measure can provide a different perspective and help results interpretation. Given the importance of nutrient removal for the PR WWTP, this study compared impact results when standardized to the removal rates for TN, TP, and total nitrogen equivalents (N eq.) (i.e., using eutrophication potential characterization factors). Table 3-6 shows the removal rates achieved for each of these three quantities by the treatment scenarios, both in terms of annual mass removal and percent removal. The difference in removal rates between each scenario is generally only 3–4% (the highest difference is for TP removal, where Scenario 2 and Scenario 3 achieve 7% better removal than Baseline), despite Scenarios 2 and 3 achieving effluent nutrient concentrations that are generally less than half of the Baseline Scenario effluent nutrient concentrations (Table 2-2). As such, when impacts are standardized to 1 kilogram of nutrient or nutrient equivalent removed (instead of 1 cubic meter of water treated) the resulting trends are largely unaffected, as illustrated in Figure 3-15.

Table 3-6. Nutrient removal performance of treatment scenarios expressed as total nitrogen (TN) removal, total phosphorus (TP) removal, and total nitrogen equivalents (N eq.) removal.

Treatment Performance Metric	Baseline	S1 - Sidestream Filtration	S2 - Tertiary Filters	S3 - Reverse Osmosis	S4 - Zero Discharge
TN (kg/yr removed)	499,576	499,576	506,281	512,987	499,576
TP (kg/yr removed)	85,833	87,845	92,204	92,204	85,833
N eq. (kg N eq./yr removed)[a]	1,387,989	1,402,675	1,439,455	1,446,094	1,387,989
TN (% removal)	95%	95%	96%	97%	95%
TP (% removal)	93%	95%	99.6%	99.6%	93%
N eq. (% removal)	95%	96%	98%	99%	95%

Treatment Performance Metric	Baseline	S1 - Sidestream Filtration	S2 - Tertiary Filters	S3 - Reverse Osmosis	S4 - Zero Discharge

[a] Refer to Appendix A.1 for method description and characterization factors.

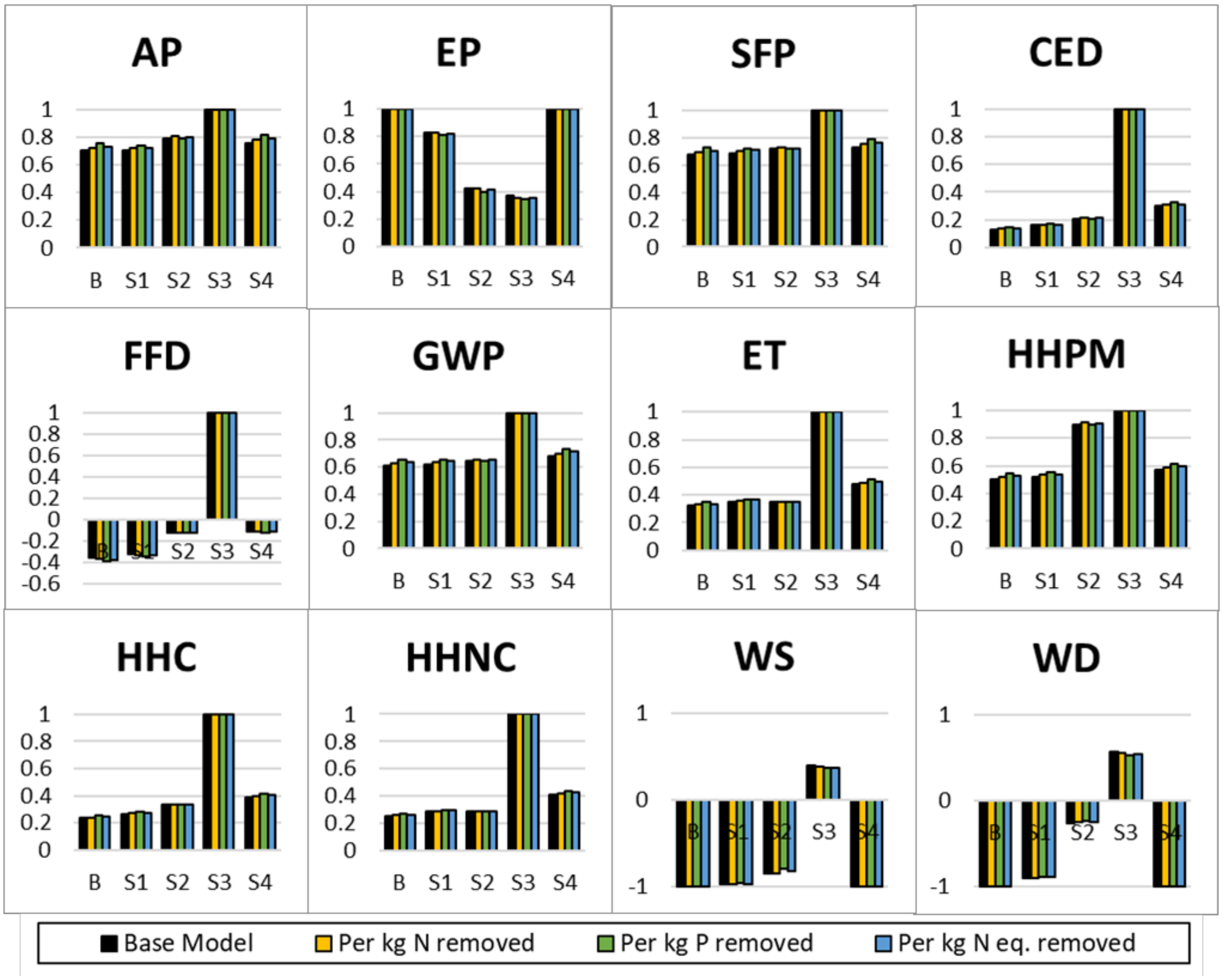

Figure 3-15. Impact results standardized to 1 cubic meter of wastewater treated (black), 1 kilogram of nitrogen removed (yellow), 1 kilogram of phosphorus removed (green), or 1 kilogram of N eq. removed (blue). All results have been normalized to the absolute value of the maximum impact/benefit for each metric/standardization approach combination, so that the largest value is 1 and the smallest value is -1.

4. Sensitivity Analysis Results and Discussion

4.1 Important Parameters

ERG performed a general parameter sensitivity analysis to evaluate the model parameters that contribute most to impacts, characterize their relative importance, and provide further context to their baseline values. This section further explains differences in impact across scenarios and, where applicable, discusses how comparable this study's results are to other, similar systems. Sensitivity results are placed in the context of parameter uncertainty ranges used in the Monte Carlo analysis (which is introduced in Section 2.3). Details on specific parameter uncertainty and uncertainty distributions can be found in Appendix B.1.

To identify important parameters, ERG reviewed the detailed contribution results illustrated in Section 3. Large impact contributions (generally >10% of total impact across multiple metrics) were traced back to individual model parameters or groups of parameters. ERG then varied each parameter individually by +/- 10% (this range is an arbitrary threshold used to test sensitivity) and recalculated impact results, isolating the effect of each parameter and providing an indication of its relative importance. Abbreviated sensitivity results are summarized in Figure 4-1 (only the top two parameters for each impact category are displayed) while full results are provided in Appendix F. Results represent the absolute value of the change in baseline environmental impact associated with each +/- 10% change in parameter value. Where possible, text in the following sections provides context on the realistic range of parameter variability for study systems.

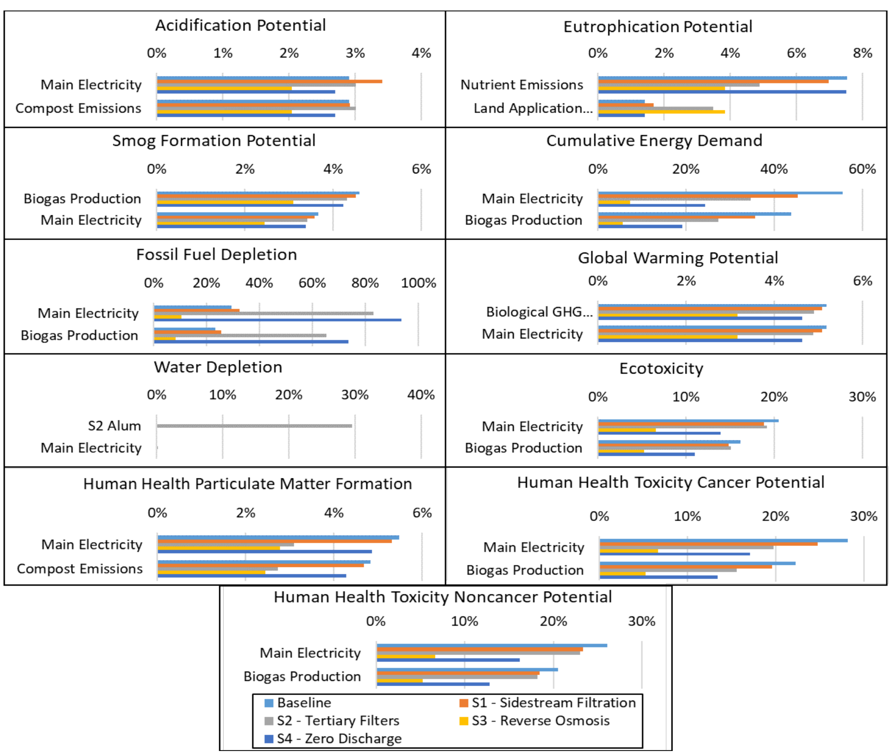

Figure 4-1. Sensitivity of top two important parameters for each impact category. For full list of parameters by impact category, see Appendix F.

4.1.1 Main Electricity

Electricity (energy use) from the main plant, consisting of electricity consumption for the core treatment facility is an important driver for nine of the 12 environmental metrics. The core treatment facility includes all primary, secondary, and sludge treatment processes. Electricity demand of tertiary treatment processes, such as deep bed media filters and MF/RO, are not included in the designated core treatment facility and are evaluated separately.

The importance of facility-wide electricity demand is not surprising and suggests that increased process control and aerator efficiency resulting from recent upgrades to the biological process support controls could have a meaningful effect on reducing impacts. The effect of core facility energy use is common to all treatment options, and therefore does not provide an opportunity to distinguish between treatment scenarios. Instead, this sensitivity result highlights the importance of maintaining or improving core facility electrical efficiency and the potential benefits available from reduced electricity consumption or reduced environmental impact of the electrical grid.

The contractor compared the energy consumption estimate for the main plant (not including additional unit processes included in Scenarios 1–4) presented in this case study against previous studies of comparable systems. Falk et al. (2013) indicates energy demand ranging from 0.5 kWh/m^3 wastewater treated for a conventional activated sludge design to 1.4 kWh/m^3 wastewater treated for an activated sludge with enhanced settling and RO. This study's LCI baseline design is similar to the conventional activated sludge design outlined in that study. PR WWTP records indicate an electricity use of 0.73 kWh/m^3 wastewater treated, falling in a similar range to Falk et al. (2013). Similarly, EPA's *Life Cycle Cost Assessments of Nutrient Removal Technologies in Wastewater Treatment Plants* study (U.S. EPA, 2021a) estimated a range of electricity use from 0.20–0.57 kWh/m^3 wastewater treated for systems ranging from a conventional activated sludge (Level 1) to systems that incorporate different types of biological nutrient removal (Levels 2 and 3). These estimates are lower than the 0.73 kWh/m^3 value used for this study, which indicates the potential to optimize electricity use at the PR WWTP.

These comparisons confirm the magnitude of electricity consumption used in this case study and suggest the results from this study may be comparable to similar facilities around the country.

4.1.2 Compost Emissions

Process emissions released during the composting process were identified as important parameters for the acidification and particulate matter formation potential impact categories. Half of produced digestate is composted with yard waste at an onsite windrow composting facility. However, only process emissions attributable to the digestate are included in the LCA model, as yard waste is a separate material, and its emissions are not attributable to the wastewater system. Ammonia is the main pollutant contributing to impact in these categories and contributes to result uncertainty.

Emission factors in the literature for ammonia range from 1.0E-4 to 0.12 kg NH_3-N per kg of feedstock N (Fukumoto et al., 2003; Hellebrand, 1998; Maulini-Duran et al., 2013). The baseline ammonia emission factor, which is the middle of the three identified values (Hellebrand, 1998), indicates that 0.044 kg of NH_3-N will be released per kg feedstock N. Another study, which presents emission factors specifically for mixtures of dewatered biosolids and green or woody waste, reports values in a comparable range but was not directly used here, as it pertains to forced-air systems (Roe et al., 2004). Variability in compost emission factors is attributable to variations in feed materials, management practices, and environmental conditions, not to system type or technology.

Uncertainty in this parameter was assessed using a lognormal distribution with a geometric standard deviation of 1.69, which results in a 95th percentile emission factor of approximately 0.1 kg NH_3-N per kg feedstock N. This emission factor is 130% greater than the baseline emission factor. Results of the sensitivity analysis indicate that if emission levels consistently fall in the high end of the range, acidification and particulate matter formation potential impacts would increase by approximately 40% and 60%, respectively, for the Baseline Scenario. Compost emissions are not affected by the selection of treatment scenario.

Compounding uncertainty in the emission factor is uncertainty in the quantity of nitrogen present in digestate entering the compost process. Plant records indicate that on average, 5.8% of digestate dry mass is nitrogen. The Monte Carlo analysis (results presented in Section 3) includes the effect of varying nitrogen content between 1.7% and 8.2% of digestate dry mass. Acidification and particulate matter formation results are less sensitive to digestate nitrogen content than they are to emission factors, which have a wider range of potential values. However, if high nitrogen contents (8.2%) and emission factors (0.1 kg NH_3-N per kg feedstock N) coincide, this can lead to an increase in acidification potential of nearly 70%. This value can be compared to the 40% increase discussed in the previous paragraph that is due only to a high emission factor. Higher digestate nitrogen content also increases the potential for land application emissions and avoided fertilizer benefits.

The included estimates of ammonia emissions are expected to be representative of typical windrow composting systems. However, given the contribution of ammonia emissions to environmental impact and the fact that they are the primary pathway for nitrogen loss during composting (Wong and Selvam, 2017), scientists are looking for ways to minimize compost ammonia emissions. A review of gaseous composting emissions indicates that use of biofilters, certain bulking agents (e.g., straw, sawdust, biochar), and lowering pH by adding phosphogypsum all hold potential to reduce ammonia emissions (Sayara and Sánchez, 2021).

4.1.3 Biogas Production

This parameter sensitivity analysis indicates that the energy and climate and toxicity metrics are sensitive to changes in biogas production. The main implication of biogas production on the LCA model relates to the potential to increase or decrease energy recovery from produced biogas. The model is informed by 47 days' worth of daily biogas production records from the PR WWTP (2019). The 25th and 75th percentile values over that period are 223,835 and 238,875 standard cubic feet per day, respectively. Both values are within 4% of mean daily biogas production, indicating relatively stable production and low potential for considerable changes in impact resulting from this source. Moreover, biogas production is expected to be consistent across treatment scenarios and therefore has more bearing on the absolute magnitude of impact results than on the relative environmental performance between treatment scenarios.

Even if biogas production remains stable across scenarios and over time, the balance of associated benefits and impacts will change according to changes in the displaced energy mix. Improvements in grid electricity environmental performance will reduce the benefits of anaerobic digestion, while displacement of dirtier electricity sources would enhance system environmental benefits.

Sensitivity results show that a 10% increase in biogas production leads to decreases of 6–44% and 8–74% in total cumulative energy demand and fossil fuel depletion impact, respectively, depending on treatment scenario. More advanced treatment scenarios, with higher energy demand, are less sensitive to changes in biogas production, as biogas energy production represents a smaller portion of total energy demand. Large changes in impact, such as the 74% decrease in the Scenario 4 FFDP, resulting from modest (10%) changes in biogas production are a result of small values of net impact. This results from a balance between impacts associated with process operation and benefits resulting from avoided product credits (see Figure 3-7 for illustration). When net impacts are small, even small changes in impact can have a large effect on impact potential. Given this and the small reported variability in daily biogas production, this parameter is not expected to strongly influence environmental impacts at the PR WWTP.

4.1.4 Nutrient Emissions

Nutrient emissions are the most sensitive parameter for the eutrophication potential impact category. The sensitivity of other impact category results to nutrient emissions is negligible. Eutrophication sensitivity results in Figure 4-1 (full results in Figure F-1) show that in Scenario 1 and the Baseline, a 10% change in TN and TP emissions leads to 7% and 7.5% changes in eutrophication potential, respectively. Scenarios with more advanced nutrient removal processes are less sensitive to a 10% change in nutrient emissions, as the absolute change in emitted nutrients is lower and other sources share more of the eutrophication burden.

For the Baseline scenario, 5 mg/L and 1 mg/L are the expected effluent concentrations for TN and TP. Expected maximum effluent concentrations are <10 mg/L and <2.5 mg/L (or <100% and <150% greater than expected average concentrations). Given the results of the sensitivity analysis reported above, if effluent concentrations of nearer to 10 mg/L and 2 mg/L are sustained over time, this would lead to an approximate 75% increase in estimated baseline eutrophication potential. However, sustained effluent concentrations in this range are not expected. In comparison, nutrient emission uncertainty in the LCI model is estimated using a lognormal distribution with a geometric standard deviation of 1.54 for all scenarios. In the Baseline Scenario, this distribution produces an 95th percentile emission value of approximately 10 mg/L for TN. Uncertainty in the technological performance of treatment processes is quantified in the blue error bars in Figure 3-2, which at their maximum represent a 46% increase relative to median eutrophication potential for the Baseline Scenario.

The LCA results presented in Section 3.1.1 use the TRACI LCIA method, which assesses generalized eutrophication applicable to both freshwater and marine environments. More detail on TRACI eutrophication modeling can be found in Section A.1. The model uses TN and TP when characterizing impact, aggregating the more specific chemical forms of both nutrients. While the current version of TRACI does not consider an availability factor (effect factor), it has been recognized that such a factor can influence specific estimates of eutrophication potential (Norris, 2002). The availability factor is a measure of bioavailability and represents the fraction of a specific chemical compound that is plant-available and therefore capable of contributing to eutrophication in a defined time period. The results of a eutrophication potential sensitivity analysis that consider nutrient bioavailability are presented in Section 4.2.

4.1.5 Land Application Emissions

Land application emissions are the second most important parameter group, next to nutrient emissions in wastewater effluent, for the eutrophication potential impact category. A 10% change in land application emissions leads to a 1.4–3.9% change in eutrophication potential, with Scenarios 2 and 3 being more sensitive. Aqueous emissions of phosphorus and nitrate contribute equally to land application eutrophication potential impact.

Generalized emission factors were used to estimate field emissions resulting from compost land application. Uncertainty exists regarding actual field emissions that would occur as a function of application rate, method, timing, and subsequent weather conditions. It is expected that this uncertainty would affect all treatment scenarios equally. The Monte Carlo analysis assesses uncertainty in land application field emissions by using identified emission factors as the mean and applying a geometric standard deviation of 1.69. Using this distribution, the 95th percentile emission factor estimates are approximately 2.5 times higher than the mean.

4.1.6 Biological GHG Emissions

GHG emissions from the biological treatment processes were identified as one of two parameter groups with the greatest influence on global warming potential. Sensitivity results show that a 10% change in process biological GHG emissions, which come from nitrous oxide and methane, lead to a 3–5% change in net global warming potential. Emissions from the biological process are constant across scenarios but have wide ranges of uncertainty. The nitrous oxide emission factor in the Baseline Scenario assumes that 0.36% of total Kjeldahl nitrogen (TKN) influent to the biological process is released as nitrous oxide. The limited sample size in Chandran (2012) found this value to vary between 0.09% and 0.62%. Baseline methane emissions are estimated using a methane correction factor (MCF) of 0.05, which represents the degree to which a system is anaerobic and capable of producing methane, with a potential range of 0 to 0.1 (IPCC, 2006).

The Monte Carlo analysis applies a lognormal distribution with a geometric standard deviation of 1.69 to the baseline estimate of nitrous oxide and methane emissions. This distribution produces a 95th percentile estimate of nitrous oxide emissions that is approximately 25% greater than the upper bound nitrous oxide emission factor reported by Chandran (2012), and a 95th percentile estimate of methane emissions that approximates the value associated with a an MCF of 0.1. As these values are 130% and 100% greater than baseline inputs, corresponding increases to GWP would be on the order of 40–70%, depending on scenario, if these emission levels were sustained over time. The described variability in emission factors indicates that uncertainty in GHG emissions has the capacity to considerably influence net GWP impact results.

4.1.7 Scenario 2 (Tertiary Filters) Alum

Alum used in the tertiary deep bed filters presented in Scenario 2 was identified as an important contributor to the water depletion and particulate matter formation impact categories. Sensitivity results show that a 10% change in alum dose leads to a 4% and 30% change in particulate matter formation and water depletion, respectively.

Considerable variation in the necessary alum dose is possible depending on the quantity of phosphorus that needs to be removed. The Baseline Scenario requires 0.95 mg/L of phosphorus removal with an uncertainty range of 0.85–2.45 mg/L using a triangular distribution, which represents a 150% increase in alum consumption at the high end of the range. In situations where prolonged use of elevated alum doses is required, impacts for the mentioned impact categories would be considerably increased.

4.1.8 Scenario 3 (RO) Electricity

Electricity use from MF and RO presented in Scenario 3 was identified as an important parameter, driving metrics such as acidification potential, particulate matter formation potential, global warming potential, ecotoxicity, human health toxicity (cancer and noncancer potential) and smog formation potential. Baseline electricity estimates for MF, RO, and brine injection are assumed to be within +/- 20% of the actual value based on the estimates provided by Carollo Engineers, which is double the +/-10% range used in the sensitivity analysis. While environmental impact results are sensitive to RO electricity demand compared to other parameters, the expected variability in electricity consumption is low compared to other important parameters (e.g., alum use, GHG emissions, nutrient emissions).

The electricity demand of RO and ancillary processes is comparable to similar systems from the literature. The estimated electricity input to the MF and RO processes in this study is 0.33 kWh/m^3 treated, while electricity input to deep well injection is 0.61 kWh/m^3 treated. Falk et al. (2013) reports electricity demand estimates for RO systems, including deep well injection, that are approximately 31% lower than estimates used in this study. Energy demand of the RO unit with deep well injection in the Falk et al. study can be roughly estimated by subtracting the energy demand of Level 4 (0.72 kWh/m^3 treated) from the energy demand of Level 5 (1.4 kWh/m^3 treated), resulting in an estimate of 0.65 kWh/m^3 treated. The Falk et al. study only assumes that 50% of effluent is treated in the MF/RO unit processes, which contributes to the observed difference in energy demand. In this study, two thirds of plant influent is sent to the MF/RO unit processes.

4.2 <u>Eutrophication Potential</u>

The baseline eutrophication potential analysis discussed in Section 3 uses average U.S. characterization factors from the TRACI 2.1 eutrophication method. These characterization factors are based on the amount of algal growth that could be caused by each nutrient if it were to reach a water body where it was limiting, assuming full bioavailability (Norris, 2002). However, research performed in recent decades suggests that a fraction of nutrient compounds found in WWTP effluent—organic nitrogen compounds in particular—may not be fully bioavailable and would thus not lead to eutrophication of receiving waters (Bronk et al., 2010; Filippino et al., 2011; Liu et al., 2012; Sattayatewa et al., 2009; Simsek et al., 2013; Urgun-Demirtas et al., 2008).

Organic nitrogen present in WWTP effluent (hereafter referred to as effluent organic nitrogen, or EON) can exist in a range of forms depending on the composition of WWTP influent, the microbial community within the WWTP, and the specific biological processes used by the WWTP. Although there is still uncertainty related to the exact source and composition of EON (Mesfioui et al., 2012; Pehlivanoglu-Mantas and Sedlak, 2008), it is likely that a considerable fraction is composed of the metabolic products of biological activity within the WWTP itself (Parkin and McCarty, 1981a, 1981b). Of those metabolic products, a portion consists of labile nitrogen-containing compounds including urea, dissolved free amino acids, and nucleic acids, which can turn over on the order of seconds to days (Bronk, 2002; Bronk et al., 2007). The more recalcitrant compounds are not as well-characterized, but research into similar marine organic nitrogen pools suggests they may persist on the order of months to years (Benner, 2002; Bronk, 2002).

EON bioavailability also depends on the range of complex interactions that can occur between it and a receiving environment. Nitrogen in otherwise recalcitrant forms can be biotically mobilized when exposed to different microbial communities, or abiotically mobilized when exposed to light or high salinities (Bronk et al., 2010; Filippino et al., 2011; Mesfioui et al., 2012). For the PR WWTP, this suggests that EON compounds that may be recalcitrant in the Santa Fe River may, over time, be biotically or abiotically acted upon in the Rio Grande, becoming bioavailable.

To determine how bioavailability of organic nitrogen may affect eutrophication potential results, a sensitivity analysis was performed. First, estimates of EON bioavailability were compiled from the literature, as shown in Table 4-1. For this analysis, we used data only from experiments that lasted 14 days or more (italicized values in Table 4-1) to be more representative of the travel time from the PR WWTP to the Gulf of Mexico, which is likely on the order of months to years. As most studies only report a range of results, we approximated the central tendency as the average of each study's minimum and maximum value. This results in an overall EON bioavailability average of 47% and range of 18–71%, compared to an assumption of 100% for baseline model results.

Table 4-1. Summary of Measured Effluent Organic Nitrogen Bioavailability.

Study	WWTP Type	Test Length (days)	Bioavailability	
			Ave.	Range
Filippino et al., 2011	BNR and five-stage Bardenpho	2	64%	31–96%
Bronk et al., 2010	Two different advanced BNR plants	2	16%	9–23%
Liu et al., 2011	Eight different BNR plants	14	*50%*	*32–68%*
Urgun-Demirtas et al., 2008	Pilot scale nitrification and TN plant	14	*40%*	*18–61%*

Study	WWTP Type	Test Length (days)	Bioavailability	
			Ave.	Range
Simsek et al., 2013	AS (min) and trickling filter (max)	28	*59%*	*47–71%*
Sattayatewa et al., 2009	Four-stage Bardenpho	14	*38%*	*28–48%*
Sensitivity Analysis[a]			**47%**	**18–71%**

[a] Minimum and maximum values from italicized values, or studies with a test length of 14 days or greater.

Table abbreviations: AS = activated sludge, BNR = biological nutrient removal, TN = total nitrogen

Following the framework introduced in Norris (2002) and Seppälä et al. (2004), the bioavailability factors in Table 4-1 were applied to the original TRACI 2.1 eutrophication potential characterization factors in the LCA model. Modified characterization factors were only applied to effluent emissions from the PR WWTP and not to other nutrient emissions in the LCI. Figure 4-2 shows these results in two formats. Panel a shows the contribution of major treatment processes, along with the mean (white dot), 5th percentile (bottom error bar), and 95th percentile (top error bar) results from the Monte Carlo simulation. For this sensitivity analysis, the Monte Carlo simulation accounted for all previously discussed base model uncertainty data, in addition to the range of bioavailability factors from Table 4-1 (a triangular distribution was assumed for EON bioavailability, as no study identified a specific distribution type). Panel b shows the contribution of individual chemical species to eutrophication potential impact. Baseline model results from Section 3 are shown as black dashes for comparison purposes.

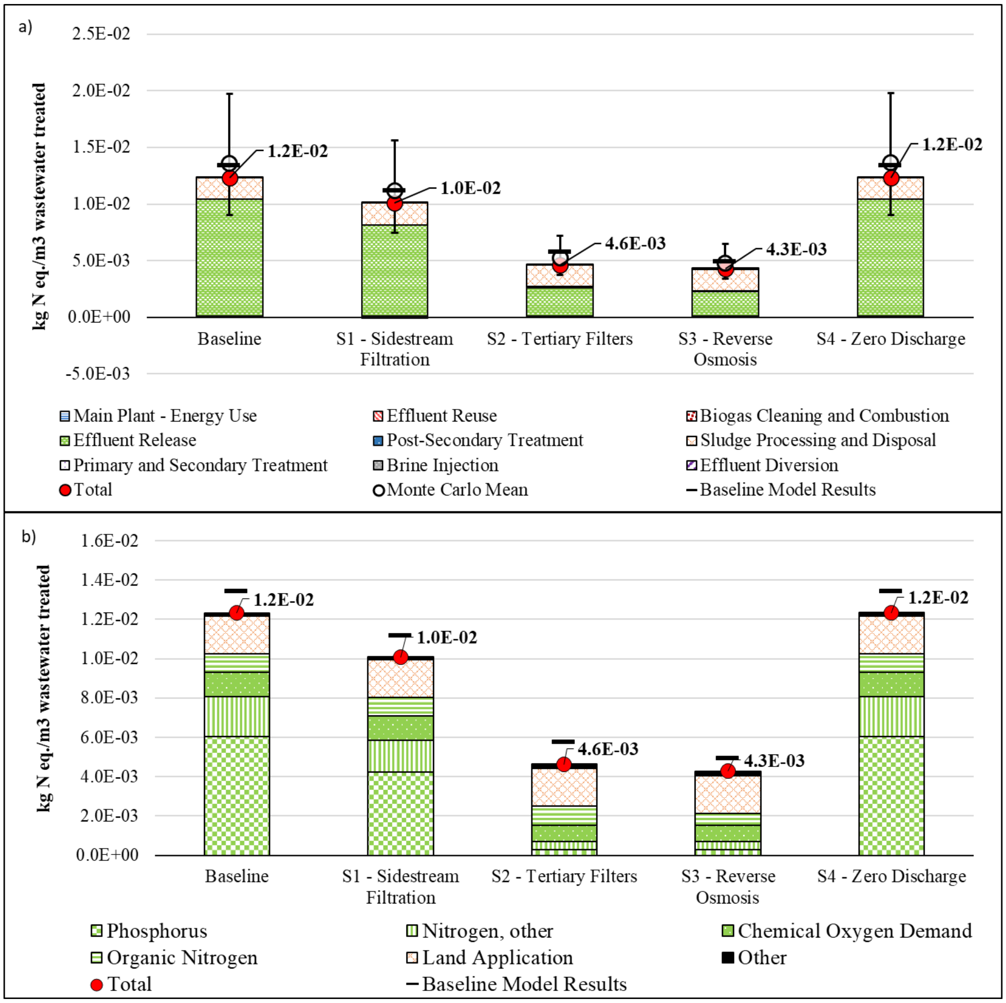

Figure 4-2. Eutrophication potential sensitivity analysis results including uncertainty ranges as the 5th and 95th percentile results from Monte Carlo simulations. Panel a shows results aggregated according to major plant process. Panel b shows contributions to eutrophication impacts from individual nutrient species.

A comparison of baseline model results (black dashes in Figure 4-2; 100% of nitrogen bioavailable) to sensitivity analysis results (47% of nitrogen bioavailable) shows that reducing the bioavailable fraction of nitrogen from 100% to 47% in the TRACI model decreased the eutrophication potential impacts for all scenarios. Decreases are largest for Scenarios 2 and 3 at 19% and 13%, respectively, while decreases for the Baseline/Scenario 4 and Scenario 1 are only 8% and 10%, respectively, as EON makes up a smaller proportion of total impacts for those scenarios. A decrease in overall impacts is important if these results are to be incorporated into a wider normalization analysis; normalized eutrophication potential impacts presented in Section 3.5 (Table 3-4, first row) would be reduced by the same amounts listed above.

Baseline model results show Scenario 3 to result in the lowest eutrophication potential impacts (4.9E-3 kg N eq./m^3), with impacts from Scenario 2 being only 16% greater (5.7E-3 kg N eq./m^3) and considerable overlap between each scenario's uncertainty range. Because organic nitrogen is the biggest difference between the effluent of Scenarios 2 and 3, applying a bioavailability factor to EON reduces the difference in impacts between these two scenarios to just 9%. These results suggest that as the bioavailability of EON decreases, eutrophication potential impacts between Scenarios 2 and 3 become more similar.

Some research on the bioavailability of phosphorus in treated wastewater has shown reduced bioavailability of certain phosphorus compounds (Li and Brett, 2015; Qin et al., 2015) and even lower bioavailability for treatment systems that use phosphorus precipitation or chemical removal processes, such as alum used in Scenario 2[16] (Ekholm and Krogerus, 1998; Li and Brett, 2012). However, bioavailability depends on the type of phosphorus compounds present in effluent (e.g., dissolved/particulate, reactive/non-reactive, hydrophobic/hydrophilic [Li and Brett, 2015; Qin et al., 2015]), the determination of which is beyond the scope of this study. Still, it is possible that the small amount of phosphorus in Scenario 2's effluent (phosphorus represents 6.5% of the total impact for Scenario 2 in Figure 4-2b) would be in a stable metal complex and relatively less bioavailable than phosphorus in other scenario effluents. This would further reduce the eutrophication impacts of Scenario 2 relative to other scenarios.

In recent decades, considerable research into the bioavailability of EON has been performed (studies reviewed here are not exhaustive). This research has been motivated, in part, by the continual advancement of wastewater nutrient removal technologies and their encroachment on technological limits of organic nitrogen removal in particular (Lewis et al., 2011). Still, methods for determining EON bioavailability are not perfect, as noted by most authors cited in Table 4-1. First, bioavailability is generally determined by a measurement of the net change in organic nitrogen concentration. Over test durations of days or weeks, researchers acknowledge there is likely continual turnover of some portion of the organic nitrogen pool (representing a contribution to biological activity) that cannot be quantified without more advanced and rarely used measurement techniques such as molecular tracking (Bronk et al., 2010; Mesfioui et al., 2012). For example, Fourier transform ion cyclotron mass spectrometry was used to show that under one 14-day bioassay experiment, 79–100% of the compounds present at the start of the experiment were replaced with new compounds produced during the experiment (Bronk et al., 2010; Mesfioui et al., 2012). Organic nitrogen can also be highly abiotically reactive (Bronk et al., 2010; Filippino et al., 2011; Mesfioui et al., 2012), resulting in partial mobilization of nitrogen under conditions that may not be simulated using standard bioassay methods. These factors suggest that the ranges of EON bioavailability reported in the literature (e.g., Table 4-1) may be underestimating its full bioavailability.

At its point of discharge, PR WWTP effluent often makes up the majority of flow in the Santa Fe River, as upstream water allocations often exceed natural flow and have resulted in the Santa Fe River being characterized an unclassified intermittent stream (NMED, 2012). As such, the ecology of the Santa Fe River downstream from the PR WWTP is highly dependent on the quality and quantity of PR WWTP effluent. An assimilative capacity study was performed from 2017 to 2018 to develop a water quality model to understand how changes in PR WWTP effluent quality would affect Santa Fe River water quality below the point of discharge (Leonard Rice Engineers, 2018). As part of the study, water quality was sampled over several seasons along a transect in the Santa Fe River. However, sampling was conducted at a time when PR WWTP

[16] Scenario 1 also uses a chemical precipitation process for phosphorus removal, but uses magnesium to precipitate phosphate ions to create struvite, which can be used directly as a bioavailable fertilizer.

effluent TN concentrations ranged from 4 to 7 mg/L and were at times dominated by ammonia, representing conditions unlike any that would be encountered in current study scenarios (where TN concentrations range from 2 to 5 mg/L with negligible ammonia concentrations). Sampling and modeling results of the assimilative capacity study suggested that the Santa Fe River downstream of the discharge point was highly dynamic because of a reach of restored wetlands, lending considerable uncertainty to how the Santa Fe River would respond under the much lower nutrient loading regimes considered in that study and here. In terms of organic nitrogen, one sample transect showed a small spike in concentration through the wetland with subsequent declines, consistent with heightened biological activity and generation of organic material in the wetland. No discussion as to the reactivity, persistence, or bioavailability of this organic nitrogen pool was provided.

Ultimately, the results of this analysis and evidence from the literature suggests that the eutrophication potential impacts from organic nitrogen could be variable in time and space. In the Santa Fe River just downstream of the PR WWTP discharge, it is possible that EON may be less bioavailable as it travels through a limited range of biotic and abiotic conditions in that river reach. Eutrophication potential impacts could therefore be towards the lower end of the range displayed in Figure 4-2, and impacts between Scenarios 2 and 3 would be more similar. However, as those compounds travel through different environments (including wetlands, the range of conditions along the length of the Rio Grande, and ultimately the Gulf of Mexico), those EON compounds will have been exposed to countless microbial consortiums, light conditions, and salinity regimes, all of which have been shown to make EON more bioavailable. In the context of a global LCA, EON bioavailability may therefore be towards the upper end of the range in Table 4-1 (71%), or greater still given the limitations of standard bioassay methods. From this wider perspective, eutrophication potential impacts may be more closely approximated by the baseline model results that assume all nutrients will, at some time, become bioavailable.

4.3 Global Warming Potential Characterization Factors

In this sensitivity analysis, the effect of using GWP factors from the two most recent IPCC Assessment Reports—the Fifth Assessment Report (IPCC, 2013) and Fourth Assessment Report (Pachauri and Reisinger, 2007)—was evaluated. GWP factors are the values used to transform the emission of all molecules that have heat trapping potential into a standardized unit. The standardization process takes CO_2 as its reference value setting its value to 1, with all other factors being set relative to that standard (i.e., kg CO_2 eq.). There are many parameters that determine CO_2 eq. values, and the scientific basis for this determination process continues to evolve, with the IPCC reviewing and updating factors as the evidence improves. Table 4-2 shows both the 2007 (AR4) and 2013 (AR5) factors for the primary GHGs resulting from the life cycle of wastewater treatment.

Table 4-2. Comparison of IPCC Assessment Report 4 and Assessment Report 5 20- and 100-year characterization factors.

Compound	Units	AR4		AR5	
		20-yr	100-yr	20-yr	100-yr
CO_2	kg CO_2 eq./kg	1	1	1	1
CH_4	kg CO_2 eq./kg	72	25	84	28
N_2O	kg CO_2 eq./kg	289	298	264	265

The effect of different GWP factors on net GWP impacts depends on the relative contribution of each GHG to the total GWP impacts of each treatment scenario. For example, GWP impacts for the Baseline Scenario are fairly evenly mixed between CO_2 emissions from electricity use and methane (CH_4) and nitrous oxide (N_2O) emissions from the biological treatment process (Section 3.2.3, Figure 3-8). Conversely, a greater proportion of impacts for Scenario 3 come from CO_2 emissions from electricity use. Therefore, total impacts from the Baseline Scenario are likely to be more sensitive to the selection of GWP factors, given the higher factor values for CH_4 and N_2O (Table 4-2).

GWP impacts for the different GWP factor scenarios are provided in Table 4-3 and illustrated in Figure 4-3. Compared to base model results, 20-year factors produce the largest increases in GWP impacts given the difference in 20-year vs. 100-year factors for CH_4. Recently, municipalities and states that track their GHG emissions have begun using 20-year factors (e.g., Howarth 2020) given the importance of methane emissions on GWP. Twenty-year factors also tend to reduce the relative difference between treatment scenarios (e.g., the relative difference in impacts between the Baseline Scenario and Scenario 3), mainly owing to the relative contributions of CH_4 and CO_2 to net impacts. Still, the relative ranking of treatment scenarios remains unchanged regardless of GWP factor selection, with the Baseline Scenario resulting in the lowest GWP impacts and Scenario 3 resulting in the highest GWP impacts.

Table 4-3. Global Warming Potential (GWP) Sensitivity Analysis Results.

GWP Model	Net Impact (kg CO_2 eq./m^3 wastewater treated)				
	Baseline	S1	S2	S3	S4
Baseline model results	0.79	0.80	0.83	0.83	0.88
AR4: 100-year	0.60	0.62	0.65	0.65	0.69
AR5: 100-year	0.62	0.64	0.67	0.67	0.72
AR4: 20-year	1.38	1.40	1.44	1.44	1.49
AR5: 20-year	1.57	1.58	1.62	1.62	1.67

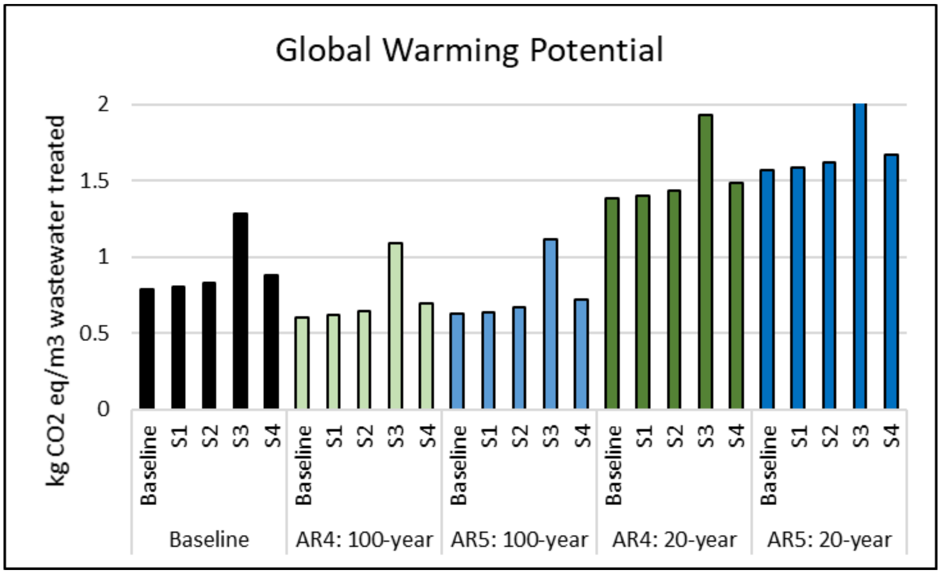

Figure 4-3. Sensitivity of global warming potential results to selection of characterization factors.

4.4 Electricity Grid Mix

In this sensitivity analysis, scenario models were run using different electrical grids to determine the sensitivity of impacts to this model parameter selection. Models were run using either a U.S. average grid mix or a 100% solar grid mix and compared to base model results, which were calculated using a regional grid reflective of local electricity production. The specific composition of the Arizona/New Mexico grid is provided in Table 2-5.

When conducting the sensitivity analysis, the electrical grid mix that serves the WWTP is varied for each treatment scenario, while the electrical grid mix associated with background processes remain constant. This is reasonable, since it is likely that background chemicals and fuels are not produced in the same region of the U.S. that they are utilized. Results for all impact categories were reproduced and compared to base model values (regional grid mix). Table 4-4 provides the results of the analysis, where the value is the percent change from the base model results. Figure 4-4 illustrates the comparisons, but instead shows results on a scale that is normalized to the absolute value of the maximum value for each metric across all scenarios, so that results can be presented on a scale of -1 to 1.

In some cases, such as the cumulative energy demand change for Scenario 4 on solar, the percent change is unusually high, which reflects a relatively large change standardized to an original net impact that was close to zero (i.e., small). Results should therefore be interpreted in a relative sense.

Changing from the regional grid to the U.S. average increases impacts for all metrics across all scenarios, except for a minor decrease (<1%) of global warming potential for Scenario 3. The largest increases result for toxicity metrics and cumulative energy demand. Conversely, changing from the regional grid to one entirely driven by solar uniformly decreases impacts. These decreases are mostly much larger in magnitude than the changes that result from switching to a U.S. average grid, illustrating the magnitude of improvements that could result from using solar electricity.

Improvements from switching to 100% solar are likely underestimated here as well, as the current modeling approach assumes that any electricity produced by the CHP system offsets solar. If, for example, only the plant was run on solar and any electricity produced from the CHP system fed into the existing regional grid, electricity offsets would be greater and net impacts would be reduced.

Table 4-4. Change in impacts as a function of electricity grid.

Metric	Baseline		S1		S2		S3		S4	
	U.S. Ave.	Solar	U.S. Ave.	Solar	U.S. Ave.	Solar	U.S. Ave.	Solar	U.S. Ave.	Solar
Eutrophication Potential	-0.1%	-1%	-0.1%	-1%	0.0%	-1.1%	0%	-2.7%	-0.1%	-0.6%
Acidification Potential	3.5%	-36%	4.0%	-37%	3.5%	-33%	10%	-49%	5.0%	-40%
Cumulative Energy Demand	3%	-269%	3%	-227%	2%	-176%	1.5%	-69%	2%	-141%
Global Warming Potential	-0.2%	-59%	-0.2%	-60%	-0.2%	-59%	-0.5%	-71%	-0.3%	-63%
Fossil Fuel Depletion	6.0%	-348%	7.4%	-396%	19%	-1023%	8.7%	-245%	31%	-1320%
Smog Formation Potential	0.8%	-42%	0.9%	-43%	0.9%	-41%	2.3%	-55%	1.3%	-46%
Ecotoxicity	17%	-242%	18%	-230%	18%	-236%	22%	-153%	19%	-196%
Human Health—Cancer Potential	23%	-332%	23%	-302%	19%	-243%	22%	-153%	23%	-240%
Human Health—Noncancer Potential	22%	-307%	22%	-285%	22%	-284%	22%	-153%	22%	-229%
Human Health—Particulate Matter Formation	16%	-43%	17%	-43%	10%	-26%	27%	-43%	23%	-46.0%
Water Depletion	0.2%	-0.8%	0.3%	-1%	1.0%	-3.1%	1.7%	-2.6%	0.4%	-0.9%

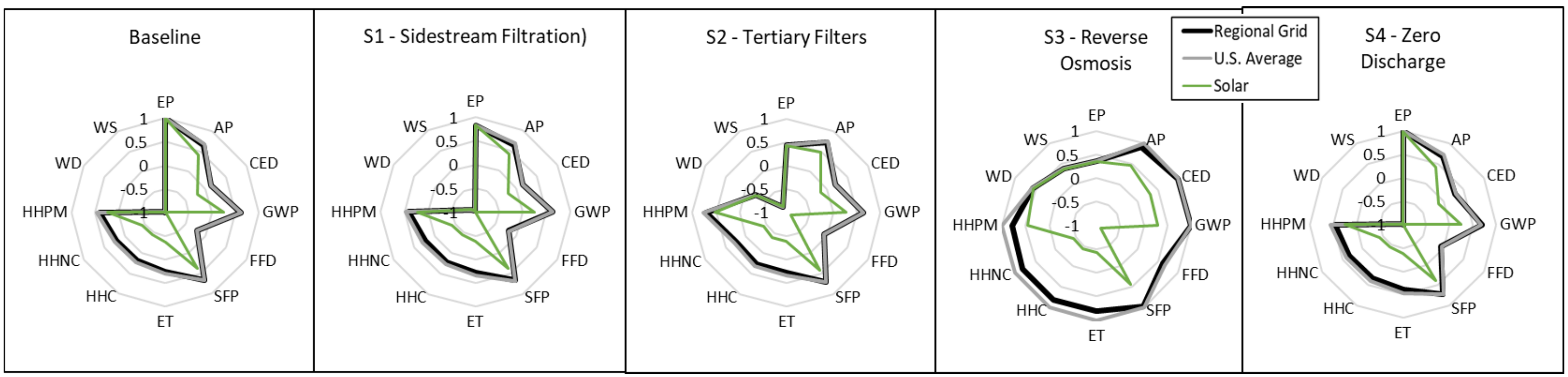

Figure 4-4. Illustration of electricity grid sensitivity analyses. Scale is normalized to the maximum value across all scenarios for each metric.

4.5 Sludge Management

The final sensitivity analysis evaluates the importance of solids handling approaches. Under base model conditions, the PR WWTP is assumed to send 50% of digestate to its composting facility and the other 50% to the local landfill. Each disposal route entails a mix of impacts and benefits. For example, composting digestate produces a usable product (compost) that can offset fertilizer production and result in lower net impacts for some metrics, including water depletion and particulate matter formation. However, the composting process produces GHGs, including N_2O and CH_4. Similarly, when digestate is landfilled, anaerobic decomposition produces CH_4 emissions contributing to global warming potential, but prevents the release of emissions contributing to eutrophication, acidification, and particulate matter formation potential.

To evaluate impact tradeoffs that may occur from the PR WWTP either composting or landfilling 100% of their digestate, ERG ran all model scenarios under both conditions. Table 4-5 summarizes the change in impacts relative to the base assumption of 50% composting and 50% landfilling. Red shading indicates an increase in impact potential relative to the baseline results, while green shading indicates improved environmental performance. Figure 4-5 illustrates the results of the sensitivity analysis, where results for each metric have been standardized to the absolute value of the largest result across all scenarios (i.e., largest positive or negative result) so that all values for that metric can be translated to a scale of -1 to 1.

Results show that impact sensitivities to the digestate processing approach are variable, as 100% composting improves global warming potential, fossil fuel depletion, smog formation potential, ecotoxicity, and water depletion; while 100% landfilling improves eutrophication potential, acidification potential, cumulative energy demand, and human health toxicities.

Compared to composting, landfilling requires less energy and results in fewer land and water impacts from nutrients or toxic pollutants if one assumes that the contents of the landfill stay sequestered indefinitely. The LCA model assumes collection and offsite treatment of landfill leachate. However, landfill liners and leachate collection systems tend to degrade over time, resulting in slow leaks and potential impacts to groundwater resources.

Although composting does require additional energy, the resulting compost is assumed to offset the need to produce traditional fertilizer, which is an energy- and water-intensive process. Accordingly, composting 100% of the PR WWTP digestate is enough to reduce net impacts for global warming potential by 4–7%, fossil fuel depletion by 2–7%, smog formation potential and ecotoxicity by 7–13%, and water depletion by 21–88%.

Table 4-5. Change in impacts as a function of solids handling assumptions.

Metric			S1		S2		S3		S4	
	100% Compost	100% Landfill	100% Compost	100% Landfill	100% Compost	100% Landfill	100% Compost	100% Landfill	100% Compost	100% Landfill
Eutrophication Potential	14%	-14%	17%	-17%	33%	-33%	39%	-39%	14%	-14%
Acidification Potential	22%	-22%	22%	-22%	19%	-19%	15%	-15%	20%	-20%
Cumulative Energy Demand	20%	-20%	16%	-16%	12%	-12%	3%	-3%	9%	-9%
Global Warming Potential	-7%	7%	-7%	7%	-7%	7%	-4%	4%	-6%	6%
Fossil Fuel Depletion	-4%	4%	-4%	4%	-11%	11%	-1%	1%	-13%	13%
Smog Formation Potential	-8%	8%	-8%	8%	-8%	8%	-5%	5%	-7%	7%
Ecotoxicity	-8%	8%	-8%	8%	-8%	8%	-5%	5%	-7%	7%
Human Health—Cancer Potential	13%	-13%	11%	-11%	9%	-9%	3%	-3%	8%	-8%
Human Health—Noncancer Potential	14%	-14%	13%	-13%	12%	-12%	4%	-4%	9%	-9%
Human Health—Particulate Matter Formation	22%	-22%	21%	-21%	12%	-12%	11%	-11%	19%	-19%
Water Depletion	-21%	21%	-24%	24%	-83%	83%	-37%	37%	-21%	21%

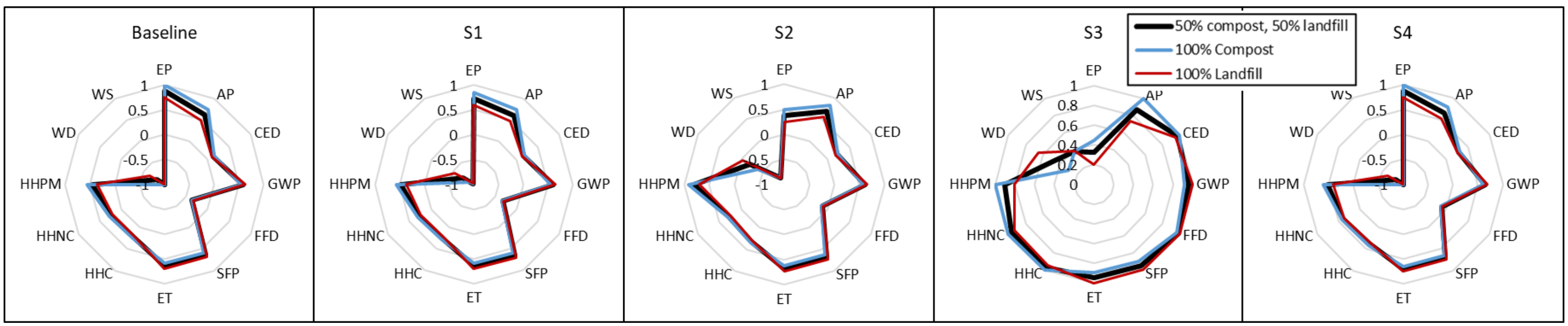

Figure 4-5. Illustration of solids handling sensitivity analyses. Scale is normalized to the maximum value across all scenarios for each metric. See Table 1-3 for abbreviation descriptions.

5. Conclusions

This study compares the environmental impact of the optimized PR WWTP (Baseline Scenario) against four potential scenarios intended to reduce nutrient pollution in the Santa Fe River. Baseline results present a best estimate of environmental performance for each treatment scenario across 12 environmental impact categories. A Monte Carlo uncertainty assessment was performed to quantify uncertainty in baseline LCA results. A parameter sensitivity analysis was carried out to identify key parameters influencing impact results in each category (Section 4.1). Additional sensitivity analyses were conducted to examine how impact results are affected by selection of eutrophication and global warming potential characterization factors, electricity grid mix, and sludge management practices.

Table 5-1 presents a summary of baseline LCA results from Section 3. For each metric, results have been standardized by dividing each result by the maximum absolute value across all scenarios so that each can be expressed on a scale of -1 to 1, where a value closest to -1 (1) represents the scenario with the best (worst) performance in a particular impact category. No weighting factors are applied in Table 5-1 or throughout this study, which implicitly gives equal weight to each of the 12 metrics.

Table 5-1. Standardized Baseline Impacts for Each Study Treatment Scenario[a].

Metric	Standardized Impact Results				
	Baseline Scenario	S1 – Sidestream Filtration	S2 – Tertiary Filters	S3 – Reverse Osmosis	S4 – Zero Discharge
Eutrophication Potential	1	0.83	0.43	0.37	1
Acidification Potential	0.7	0.7	0.79	1	0.76
Cumulative Energy Demand	0.13	0.16	0.21	1	0.3
Global Warming Potential	0.61	0.62	0.65	1	0.68
Fossil Fuel Depletion	-0.36	-0.33	-0.13	1	-0.11
Smog Formation Potential	0.68	0.69	0.72	1	0.73
Ecotoxicity	0.32	0.35	0.35	1	0.48
Human Health Toxicity—Cancer Potential	0.24	0.27	0.34	1	0.39
Human Health Toxicity—Noncancer Potential	0.25	0.28	0.29	1	0.41
Human Health—Particulate Matter Formation	0.51	0.52	0.9	1	0.57
Water Depletion	-1	-0.9	-0.26	0.57	-1
Water Scarcity	-1	-0.98	-0.86	0.39	-1

a – See Section 2 for a definition of metrics. Standardized baseline impacts obtained for each metric by dividing each result by the maximum absolute value of that metric across all scenarios. For each metric, the value closest to -1 represents the scenario with the best performance in a particular category, while the value closest to 1 represents the scenario with the worst performance. Standardized scales are meant to convey a measure of the relative performance of scenarios across individual metrics. For full, unstandardized results, see Section 3.

Project goals emphasize the importance of eutrophication potential impacts among the 12 considered environmental metrics. LCA results show that Scenario 3 (RO) results in the lowest eutrophication potential impacts. Baseline eutrophication potential results for Tertiary Filtration indicate similar performance to RO, especially when considering results of the Monte Carlo uncertainty assessment. As expected, eutrophication potential impacts are greatest for the Baseline and Zero Discharge Scenarios, which represent current, optimized operation of the PR WWTP and are only differentiated in terms of their discharge locations, not in the amount of nutrient removal they provide. The Sidestream Filtration scenario realizes a 17% improvement in eutrophication potential impact relative to the Baseline. The eutrophication potential sensitivity analysis, which examines the influence of assumptions related to organic nitrogen bioavailability, shows that the ranked performance of treatment scenarios remains unchanged. However, the difference in impacts between Tertiary Filtration and RO is reduced, indicating that when lower bioavailability of EON is assumed, the relative performance of Tertiary Filtration improves.

Table 5-1 shows that reductions in nutrient pollution and eutrophication potential associated with RO come at the expense of higher environmental impacts in all other environmental categories (relative to the Baseline Scenario). While the same is true for Tertiary Filtration, the magnitude of increases in environmental impact (relative to the Baseline Scenario) are considerably reduced. Zero Discharge only results in a small increase in impacts relative to the Baseline Scenario, owing to the additional energy that would be required to pump all effluent that is not reused to the Rio Grande, but results in no reduction in eutrophication potential. The moderate reduction in eutrophication potential associated with Scenario 1 (filtrate treatment) comes at the expense of only minor increases in other environmental impacts. In terms of impact per unit of nutrient removed, Scenario 1 is most similar to the baseline and is more efficient across most metrics than Scenarios 2–4 (this can also be seen in Section 3.5.3, Figure 3-15).

The uncertainty assessment identifies several items not captured in the baseline results presented in Table 5-1. It was stated above that Scenario 3 has higher impacts than all other Scenarios for all impact categories except for eutrophication potential. However, Scenario 2 could result in comparable impacts to Scenario 3 for water depletion and particulate matter formation due to uncertainty in the amount of chemicals needed to sufficiently reduce phosphorus effluent concentrations. The relative similarity of water depletion impacts between Scenarios 2 and 3 is, however, eliminated, when local water scarcity is considered. Water scarcity impact results show much greater potential impacts for Scenario 3 than all other scenarios due to brine disposal in water-scarce New Mexico, which renders water associated with the injected brine unavailable for other purposes.

For human health toxicity cancer and noncancer potentials, which are driven by metal discharges, there is uncertainty regarding the expected metals removal performance of the Baseline Scenario, Scenario 1, Scenario 2, and Scenario 4 that suggest impacts could be higher in all those scenarios compared to Scenario 3. Data on metal effluent concentrations (Table 2-2) show maximum concentrations that are typically 1 to 3 orders of magnitude greater than average concentrations. The influence of these outliers would likely be minimal under average operating conditions, and toxicity cancer and noncancer potential impacts would likely be closer to the expected baseline value for each scenario.

In Section 3.5.1, this study normalized LCA results based on U.S. per capita impacts (Lippiatt et al., 2013; Ryberg et al., 2014) for the subset of metrics for which normalization factors are available. Normalization is one way to identify the impact categories that are most strongly influenced by the study system relative to typical emission rates for the wider region or, in this case, country. Eutrophication potential impacts make up the largest contribution compared to typical U.S. per capita impacts, ranging from 2 to 5%. This indicates that 2–5% of per capita eutrophying emissions are attributable to the wastewater treatment services as provided by the scenarios considered in this study. Normalized water depletion results demonstrate the widest variability across treatment scenarios, with a minimum normalized impact of -2% for Scenarios 1 and 4, and a maximum normalized impact of 1.2% for Scenario 3. Water depletion results do not account for local water scarcity, which would place further emphasis on the importance of this inventory metric in the Santa Fe region. Normalized global warming potential, acidification potential, and smog formation potential contribute less than 1% to total per capita impact in each category. Normalization results therefore suggest that the choice of treatment system will be most consequential for eutrophication and water depletion impacts.

Additional sensitivity analyses performed confirm the relative performance of treatment scenarios that are reflected in the baseline results. However, the magnitude of differences between treatment scenario impacts are influenced by sensitivity assumptions. The electricity grid mix sensitivity analysis shows that if each scenario used electricity generated from 100% solar power, potential impacts of Scenario 3 are much more comparable to other scenarios across most metrics (potential impacts remain highest for water depletion and water scarcity). Standardizing impact results to different measures of nutrients removed (Section 3.5.3) also results in negligible change to the relative ranking of impacts across scenarios.

Certain potential environmental impacts associated with the RO treatment process (Scenario 3) were not captured in this study but are worth noting. First, the RO treatment process produces treated wastewater (RO permeate) with low levels of total dissolved solids that, without modification, can be corrosive to equipment, leach metals from geological substrates, and be toxic to aquatic organisms. This is of particular concern when RO permeate constitutes a considerable share of total flow as would be the case seasonally in the Santa Fe River. Treated RO effluent should be blended with natural waters (e.g., Rio Grande water) to increase total dissolved solids and base ion concentrations such that effluent does not negatively impact receiving environments. While beyond the scope of this study, other options exist for the reuse and management of treated effluent, such as direct potable reuse or aquifer recharge. These effluent reuse scenarios would likely reduce flow to the Santa Fe River and entail additional impacts and benefits not considered here.

The second potential environmental impact of RO that was not captured in this study is that the LCA model for Scenario 3 only considers impacts of brine disposal associated with the energy required for deep well injection and water depletion. Water depletion impacts assume that disposed brine is taken out of the local water cycle and does not mix with groundwater resources. RO brine can be highly corrosive and is, by definition, a concentrated form of the constituents that have been separated from the permeate that could lead to additional impacts to groundwater resources (Ahmed et al., 2001; Chelme-Ayala et al., 2009). If RO brine intrudes into groundwater aquifers used for drinking water or is otherwise mobilized in the environment, current impact results would likely underestimate environmental impacts associated with brine disposal.

One of the key challenges of the interpretation phase of an LCA study is consideration of environmental/economic tradeoffs and how an individual or institutional decision-maker can or should weigh impacts across multiple metrics. Weighting of environmental impacts can be used to synthesize LCA results and determine the best option among alternatives. This study does not apply weighting factors, nor should the implicit equal weighting in Table 5-1 or elsewhere in this report be taken as an endorsement of equal importance across economic and environmental metrics. As a next step, stakeholders should explore the incorporation of weighting factors so that the results presented in this study can be used more directly within a decision-making framework.

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APPENDIX A
LIFE CYCLE IMPACT ASSESSMENT

Appendix A – Life Cycle Impact Assessment

LCIA is defined in ISO 14044 section 3.4 as the "phase of life cycle assessment aimed at understanding and evaluating the magnitude and significance of the potential environmental impacts for a product system throughout the life cycle of the product (ISO, 2006b)." Within LCIA, the multitude of environmental LCI flows throughout the entire study boundaries (e.g., raw material extraction through chemical and energy production and through wastewater treatment and effluent release) are classified according to whether they contribute to each of the selected impact categories. Following classification, all the relevant pollutants are normalized to a common reporting basis, using characterization factors that express the impact of each substance relative to a reference substance. One well known example is the reporting of all GHG emissions in CO_2-eq. The LCI and LCIA steps together compromise the main components of a full LCA.

ISO 14040 recommends that an LCA be as comprehensive as possible so that "potential trade-offs can be identified and assessed (ISO, 2006a)." Given this recommendation, this study applies a wide selection of impact categories that encompass both environmental and human health indicators. The selected LCIA categories address impacts at global, regional, and local scales.

This study considers 12 impact categories in assessing the environmental burdens of the nine wastewater treatment configurations. The majority of impact categories address air and water environmental impacts, while three of the selected impact categories are human health impact indicators. There are two main methods used to develop LCIA characterization factors: midpoint and endpoint. The impact categories selected for this study are all midpoint indicators. Midpoint indicators are directly associated with a specific environmental or human health pathway. Specifically, midpoint indicators lie at the point along the impact pathway where the various environmental flows that contribute to these issues can be expressed in a common unit (e.g., CO_2-eq). Units such as CO_2 equivalents express a relevant environmental unit, in this case radiative forcing (W-yr/m^2/kg), in the context of a reference substance. This is mentioned to reinforce the fact that there are physical mechanisms underlying all of the impact assessment methods put forward. Endpoint indicators build off of these midpoint units and translate them into impacts more closely related to the final damage caused by the substance, which include: (1) human health, (2) man-made environment, (3) natural environment, and (4) natural resources (Udo de Haes et al., 1999). It is commonly believed that endpoint indicators are easier for many audiences to understand, but suffer due to the fact that they significantly increase the level of uncertainty associated with the results because the translation to final damage are typically less understood and lack data. To reduce uncertainty of the results, this work generally focuses on indicators at the midpoint level.

The LCIA method provided by the Tool for the Reduction and Assessment of Chemical and Environmental Impacts (TRACI), version 2.1, developed by the U.S. EPA specifically to model environmental and human health impacts in the U.S., is the primary LCIA method applied in this study (Bare, 2012). Additionally, the ReCiPe LCIA method is recommended to characterize fossil fuel depletion and water depletion (Goedkoop et al., 2009). Energy is tracked based on point of extraction using the cumulative energy demand method developed by ecoinvent (Ecoinvent Centre, 2010a).

Summaries of each of the 12 impact categories evaluated as part of this study are provided in the subsequent sections. Each summary includes a table of the main substances considered in the impact category, associated substance characterization factor, and the compartment (e.g., air, water, soil) the substance is released to or extracted from (in the case of raw materials). These tables highlight key substances but should not be considered comprehensive.

A.1 Eutrophication Potential

Eutrophication occurs when excess nutrients (e.g., nitrogen or phosphorus) are introduced to surface and coastal water causing the rapid growth of aquatic organisms. This growth (generally referred to as an "algal bloom") reduces the amount of dissolved oxygen in the water, thus decreasing oxygen available for other aquatic species. Eutrophication can lead to several negative endpoint effects on human and ecosystem health. Oxygen depletion or changing nutrient availability can affect species composition and ecosystem function. Additionally, the proliferation of certain algal species can result in toxic releases that directly impact human health (Henderson, 2015).

Table A-1 provides a list of common substances that contribute to eutrophication, along with their associated characterization factors. As indicated in the table, air emissions can also contribute to eutrophication, through the atmospheric deposition of nitrogen compounds. The TRACI 2.1 eutrophication method considers emissions to both fresh and coastal waters. TRACI 2.1 characterization factors for eutrophication are the product of a nutrient factor and a transport factor (Bare et al., 2003). The nutrient factor is based on the amount of potential algae growth caused by each pollutant. The relative eutrophying effect of a nitrogen or phosphorus species is determined by its stoichiometric relationship to the Redfield ratio (Norris, 2002). The Redfield ratio is the average C:N:P ratio of phytoplankton, and describes the necessary building blocks to facilitate algal growth and reproduction (Redfield, 1934). The transport factor accounts for the likelihood that the pollutant will reach a body of water based on the average hydrology considerations for the U.S. The transport factor is used to account for the fact that not all the nutrient released will reach aquatic systems and supply limiting nutrients. Both air and water emissions have the potential to contribute to eutrophication; however, the fraction of air emissions which make their way into bodies of water is often lower, which is reflected in a smaller transport factor, and the correspondingly lower characterization factors of nitrogen oxide air emissions in Table 4-1.

Both BOD and COD are also shown in Table A-1 as contributing to eutrophication impacts. Although the mechanism of oxygen consumption differs from that associated with nutrient emissions of nitrogen and phosphorus, the result remains the same. Only COD (and not BOD) values are characterized in this study to avoid double-counting (Norris, 2002).

In this study, U.S. average characterization factors are used, which are created as a composite of all water basins in the U.S. For a discussion of the procedure used to produce composite U.S. characterization factors, see Norris (2002). It must be recognized that context specific features of an individual WWTP and the hydrology and ecology of the watershed in which it is located could serve to ameliorate or increase site-specific impacts. In addition, water body-specific nutrient limitations and local transport characteristics tend to be the most decisive factors in determining regional differences in eutrophication impacts (Henderson, 2015).

Table A-1. Main Pollutants Contributing to Eutrophication Potential Impacts (kg N eq/ kg Pollutant).

Pollutant	Chemical Formula	Compartment	Characterization Factor
Biological oxygen demand (BOD_5)	N/A	Water	0.05
Chemical oxygen demand (COD)	N/A	Water	0.05
Ammonia	NH_3	Water	0.78
Nitrate	NO_3-	Water	0.24
Nitrogen dioxide	NO_2	Air	0.04
Nitrogen monoxide	NO	Air	0.04
Nitrogen oxides	NO_x	Air	0.04
Nitrogen, organic bound	N/A	Water	0.99
Phosphate	PO_4^{3-}	Water	2.4
Phosphorus [a]	P	Water	7.3
Selected Method—			TRACI 2.1

[a] Represents phosphorus content of unspecified phosphorus pollutants (e.g., "total phosphorus" in effluent composition).

A.2 Cumulative Energy Demand

The cumulative energy requirements for a system can be categorized by the fuels from which energy is derived. This method is not an impact assessment, but rather is a cumulative inventory of all energy extracted and utilized. Energy sources consist of non-renewable fuels (natural gas, petroleum, nuclear and coal) and renewable fuels. Renewable fuels include hydroelectric energy, wind energy, energy from biomass, and other non-fossil sources. Cumulative energy demand (CED) includes both renewable and non-renewable sources as well as the embodied energy in biomass and petroleum feedstocks. CED is measured in MJ/kg. Energy is tracked based on the higher heating value (HHV) of the fuel at the point of extraction. Table A-2 includes a few examples of fuels that contribute to CED in this project and their associated characterization factors.

Table A-2. Main Energy Resources Contributing to Cumulative Energy Demand.

Energy Resource	Compartment	Units	Characterization Factor
Energy, gross calorific value, in biomass	Resource (biotic)	MJ/MJ	1.0
Coal, hard, unspecified, in ground	Resource (in ground)	MJ/kg	19
Gas, natural, in ground	Resource (in ground)	MJ/kg	47
Oil, crude, in ground	Resource (in ground)	MJ/kg	46
Selected Method—		Ecoinvent	

A.3 Global Warming Potential

Global warming refers to an increase in the earth's temperature in relation to long-running averages. In accordance with IPCC recommendations, TRACI's GWP calculations are based on a 100-year time frame and represent the heat-trapping capacity of the gases relative to an equal weight of carbon dioxide. Relative heat-trapping capacity is a function of a molecule's radiative forcing value as well as its atmospheric lifetime. Table A-3 provides a list of the most common GHGs along with their corresponding GWPs, or CO_2 equivalency factors, used in TRACI 2.1. Contributing elementary flows can be characterized using GWPs reported by the IPCC in either 2007 (Fourth Assessment Report) or in 2013 (Fifth Assessment Report) (IPCC, 2007; IPCC, 2013). While the 2013 GWPs are the most up-to-date, the 2007 GWPs have been officially adopted by the United Nations Framework Convention on Climate Change (UNFCCC) for international greenhouse gas reporting standards and are used by EPA in their annual greenhouse gas emissions report. The baseline results in this study apply the 2007 GWPs, but results with the 2013 GWPs are provided in a sensitivity analysis in Section 4.2.

Table A-3. Main Greenhouse Gas (GHG) Emissions Contributing to Global Warming Potential Impacts ($kg\ CO_2$ eq/kg GHG).

GHG	Chemical Formula	Compartment	GWP (IPCC 2007)	GWP (IPCC 2013)
Carbon dioxide	CO_2	Air	1.0	1.0
Nitrous oxide	N_2O	Air	3.0E+2	2.7E+2
Methane	CH_4	Air	25	28
Sulfur hexafluoride	SF_6	Air	2.3E+4	2.4E+4
Selected Method—			IPCC 2007 or 2013 100a	

A.4 Acidification Potential

The deposition of acidifying substances such as those listed in Table A-4 have an effect on the pH of the terrestrial ecosystem. Each species within these ecosystems has a range of pH tolerance, and the acidification of the environment can lead to shifting species composition over time. Acidification can also cause damage to buildings and other human infrastructure (Bare, 2012). The variable buffering capacity of terrestrial environments yields a correspondingly varied response per equivalent unit of acidification. Due to a lack of data, the variable sensitivity of receiving regions is not captured in TRACI characterization factors (Norris, 2002). The acidification method in TRACI utilizes the results of an atmospheric chemistry and transport model, developed by the US National Acid Precipitation Assessment Program (NAPAP), to estimate total North American terrestrial deposition of expected SO_2 equivalents due to atmospheric emissions of NO_x and SO_2 and other acidic substances such as HCl and HF, as a function of the emissions location (Bare et al., 2003). Emissions location is modeled in this study as average U.S. using TRACI's composite annual North American emissions average of U.S. states.

Table A-4. Main Pollutants Contributing to Acidification Potential Impacts ($kg\ SO_2$ eq/kg Pollutant).

Pollutant	Chemical Formula	Compartment	Characterization Factor
Sulfur dioxide	SO_2	Air	1.0
Ammonia	NH_3	Air	1.9
Nitrogen dioxide	NO_2	Air	0.70
Nitrogen oxides	NO_x	Air	0.70
Hydrogen chloride	HCl	Air	0.88
Hydrogen fluoride	HF	Air	1.6
Hydrogen sulfide	H_2S	Air	1.9
Selected Method—		TRACI 2.1	

A.5 Fossil Depletion

Fossil depletion is a measure of the study systems demand for non-renewable energy resources. As non-renewable resources, the availability of fossil energy will not change (i.e., new fossil energy will not be produced) on relevant human timescales. When these resources are depleted and resource quality declines, the cost and environmental impact of accessing a given quantity of energy increases. Fossil depletion is measured in kg oil equivalent based on each fuel's heating value. Renewable energy systems and uranium are not included in the fossil depletion metric, but are assessed within the CED methodology previously discussed. Table A-5 presents common fossil fuel flows and their associated characterization factors for this impact category.

Table A-5. Main Fossil Fuel Resource Contributing to Fossil Depletion (kg oil eq/kg Fossil Fuel Resource).

Fossil Fuel Resource	Compartment	Characterization Factor
Oil, crude, 42 MJ per kg	Resource (in ground)	1.0
Coal, 18 MJ per kg	Resource (in ground)	0.43
Coal, 29.3 MJ per kg	Resource (in ground)	0.70
Gas, natural, 30.3 MJ per kg	Resource (in ground)	0.72
Gas, natural, 35 MJ per m3	Resource (in ground)	0.83
Methane	Resource (in ground)	0.86
Selected Method—		ReCiPe

A.6 Smog Formation Potential

The smog formation impact category characterizes the potential of airborne emissions to cause photochemical smog. The creation of photochemical smog occurs when sunlight reacts with NO_x and volatile organic compounds (VOCs), resulting in tropospheric (ground-level) ozone (O_3) and particulate matter. Potential endpoints of such smog creation include increased human mortality, asthma, and deleterious effects on plant growth. Smog formation potential impacts are measured in kg of O_3 equivalents. Table A-6 includes a list of smog forming chemicals expected to be associated with this project along with their characterization factors.

Table A-6. Main Pollutants Contributing to Smog Formation Impacts (kg O_3 eq/kg Pollutant).

Pollutant	Chemical Formula	Compartment	Characterization Factor
Sulfur monoxide	SO	Air	1.0
Carbon monoxide	CO	Air	0.06
Methane	CH_4	Air	0.01
Nitrogen dioxide	NO_2	Air	17
Nitrogen oxides	NO_x	Air	25
Volatile organic compounds (VOCs)	N/A	Air	3.6
Selected Method—			TRACI 2.1

A.7 Human Health—Particulate Matter Formation Potential

Particulate matter (PM) emissions have the potential to negatively impact human health. Respiratory complications are particularly common among children, the elderly, and individuals with asthma (U.S. EPA, 2008a). Respiratory impacts can result from a number of types of emissions including PM10, PM2.5, and precursors to secondary particulates such as sulfur dioxide and nitrogen oxides. Respiratory impacts are a function of the fate of responsible pollutants as well as the exposure of human populations. Table A-7 provides a list of common pollutants contributing to impacts in this category along with their associated characterization factors. Impacts are measured in relation to PM2.5 emissions.

Table A-7. Main Pollutants Contributing to Human Health—Particulate Matter Formation Potential (kg PM2.5 eq/kg Pollutant)

Pollutant	Chemical Formula	Compartment	Characterization Factor
Particulates, < 2.5 um	N/A	Air	1.0
Particulates, > 2.5 um, and < 10um	N/A	Air	0.23
Ammonia	NH_3	Air	0.07
Nitrogen oxides	NO_x	Air	7.2E-3
Sulfur oxides	SO_x	Air	0.06
Selected Method—			TRACI 2.1

A.8 Water Depletion

Water depletion results are displayed on a consumptive basis (i.e., depletion). When water is withdrawn from one water source and returned to another watershed this is considered consumption, as there is a net removal of water from the original water source. For instance, it is assumed that deepwell injection of the brine fluid from RO is consumptive water depletion, since water is being diverted from a watershed making it unavailable for subsequent environmental or human uses. Consumption also includes water that is withdrawn and evaporated or incorporated into the product. Cooling water that is closed-loop circulated, and does not evaporate, is not considered consumptive use. Water depletion is only included as an inventory category in this study, which is a simple summation of water inputs. The analysis does not attempt to assess water-related damage factors. For instance, there is no differentiation between water depletion that occurs in water-scarce or water-abundant regions of the world. Water depletion in this study includes values for upstream fuel and electricity processes. In addition to water depletion associated with thermal generation of electricity from fossil and nuclear fuels, the water depletion for power generation includes evaporative losses due to establishment of dams for hydropower. Table A-8 shows some of the common flows associated with water depletion along with their characterization factors. Section 3.3.1 also discusses some of the uncertainty associated with calculating water depletion in LCA.

Table A-8. Main Water Flows Contributing to Water Depletion.

Water Flow	Compartment	Units	Characterization Factor
Water, lake	Resource (in water)	m^3 H_2O/m^3	1.0
Water, river	Resource (in water)	m^3 H_2O/m^3	1.0
Water, unspecified natural origin	Resource (in water)	m^3 H_2O/m^3	1.0
Water, well, in ground	Resource (in water)	m^3 H_2O/m^3	1.0
Water, unspecified natural origin/kg	Resource (in water)	m^3 H_2O/kg	1.0E-3
Selected Method—		ReCiPe	

A.9 Water Scarcity

The AWARE method is used to assess water scarcity impact. The water scarcity indicator seeks to answer the question, "what is the potential to deprive another freshwater user (human or ecosystem) by consuming freshwater in this region?" (Boulay et al., 2018). AWARE water scarcity factors, depicted in Table A-9, are applied on top of the water depletion inventory values that result from application of the method described in Section A.8. Water scarcity factors are developed based on the inverse of Availability Minus Demand ($\frac{1}{AMD}$). AMD subtracts human and ecosystem water requirements from the total availability of water in a region and divides the resulting quantity by the area of that region. Characterization factors are developed by dividing the regional AMD inverse by the corresponding world average value, resulting in a dimensionless value termed m^3 world equivalents. When the demand for water exceeds availability in a given region the value of the characterization factor is set at a maximum value of 100, as is the case for Santa Fe. Physical interpretation of this maximal value for the Santa Fe region means that the Santa Fe region has 100 "times less water remaining per area within a certain period of time as the world average" (Boulay et al., 2018).

Table A-9. Main Water Flows Contributing to Water Depletion.

Region of Withdrawal	Compartment	Units	Characterization Factor
Santa Fe, New Mexico	Resource (in water)	m^3 world equivalents/m^3	100
AZNM Electrical Grid, Generation	Resource (in water)	m^3 world equivalents/m^3	80.3
WECC Electrical Grid, Generation	Resource (in water)	m^3 world equivalents/m^3	42.2
AZNM Electrical Grid, Consumption	Resource (in water)	m^3 world equivalents/m^3	52.0
U.S., National Average	Resource (in water)	m^3 world equivalents/m^3	17.3
Selected Method—		AWARE	

A.10 Human Health—Cancer Potential

Carcinogenic human health results in this study are expressed on the basis of Comparative Toxic Units (CTU_h) based on the USEtox™ method (Huijbregts et al. 2010). Characterization factors within the USEtox™ model are based on fate, exposure, and effect factors. Each chemical included in the method travels multiple pathways through the environment based on its physical and chemical characteristics. The potential for human exposure (e.g., ingestion or inhalation) varies according to these pathways. The effect factor characterizes the probable increase in cancer-related morbidity for the total human population per unit mass of a chemical emitted (i.e., cases per kg) (Rosenbaum et al., 2008). The full USEtox™ model contains over 3,000 chemicals of global relevance, and is the product of an international project to harmonize the approach to evaluation of toxicity effects. The USEtox™ model develops characterization factors at the continental and global scale. The exclusion of more localized parameters is justified in that it was found during the harmonization process that site-specific parameters have a far lower impact on results than do the substances themselves.

Global midpoint characterization factors are employed from the most recent version of USEtox™ available in OpenLCA, version 2.02. An updated version of USEtox™, version 2.11, was released in April 2019. Characterization factors for the heavy metals, toxic organics and DBPs were updated in the OpenLCA USEtox™ LCIA method to match version 2.11. All other characterization factors remain at the default value for OpenLCA's USEtox version 2 (recommended+interim) database. Not all heavy metals, toxic organics and DBPs have established characterization factors in the USEtox™ method. Several additional sources were used to identify appropriate characterization factors. When no appropriate characterization factor was identified, the pollutant was assigned a characterization factor equal to the median characterization factor for its trace pollutant group. For illustration purposes, Table A-10 lists five of the primary chemicals that contribute to cancer, human health impacts in the US and Canada (Ryberg, 2013) along with their associated characterization factors.

The developers of the USEtox™ method are clear to point out that some of the characterization factors associated with human health effects should be considered interim, owing to uncertainty in their precise values ranging across one to three orders of magnitude. Sources of uncertainty are often attributable to the use of one exposure route as a proxy for another (route-to-route extrapolation). For a more detailed discussion of uncertainty present in these models, see the USEtox™ User's Manual (Huijbregts et al., 2010). Appropriate interpretation of results must consider the uncertainty associated with the use of interim characterization factors.

Table A-10. Main Pollutants Contributing to Human Health—Cancer Potential Impacts (CTU_h/kg Pollutant).

Pollutant	Chemical Formula	Compartment	Characterization Factor
Arsenic	As	Soil	1.8E-4[a]
Formaldehyde	CH_2O	Air	2.5E-5
Chromium VI	Cr	Soil	5.0E-3[a]
Chromium VI	Cr	Air, urban	3.8E-3[a]
Chromium VI	Cr	Water	0.01[a]
Selected Method—			USEtox™ 2.11

a – Designates an interim characterization factor.

A.11 Human Health—Noncancer Potential

Non-carcinogenic human health results in this study are expressed on the basis of Comparative Toxic Units (CTU_h) based on the USEtox™ method, which is incorporated in TRACI 2.1. The impact method characterizes the probable increase in noncancer related morbidity for the total human population per unit mass of a chemical emitted (i.e., cases per kg) (Rosenbaum et al., 2008). These impacts are calculated using the same approach as that taken for human health - cancer (Section A.10).

Global midpoint characterization factors are employed from the most recent version of USEtox™ available in OpenLCA, version 2.02. An updated version of USEtox™, version 2.11, was released in April 2019. Characterization factors for the heavy metals, toxic organics and DBPs were updated in the OpenLCA USEtox™ LCIA method to match version 2.11. All other characterization factors remain at the default value for OpenLCA's USEtox version 2 (recommended+interim) database. Not all heavy metals, toxic organics and DBPs have established characterization factors in the USEtox™ method. Several additional sources were used to identify appropriate characterization factors. When no appropriate characterization factor was identified, the pollutant was assigned a characterization factor equal to the median characterization factor for its trace pollutant group. For illustration purposes, Table A-11 lists the main chemicals contributing to noncancer, human health impacts (Ryberg, 2013) along with their associated characterization factors.

As is discussed in Section A.10, uncertainty in USEtox factors can range across one to three orders of magnitude for interim characterization factors, which are identified in Table

A-11. At the current time, all characterization factors for metal compounds are considered interim. Appropriate interpretation of results must consider the uncertainty associated with the use of interim characterization factors.

Table A-11. Main Pollutants Contributing to Human Health—Noncancer Potential Impacts (CTU_h/kg Pollutant).

Pollutant	Chemical Formula	Compartment	Characterization Factor
Acrolein	C_3H_4O	Soil	3.4E-5
Zinc, ion	Zn^{2+}	Soil	1.4E-4[a]
Arsenic, ion	As^{3+}	Soil	0.01[a]
Zinc, ion	Zn^{2+}	Air, urban	5.7E-3[a]
Mercury (+II)	Hg(II)	Air, urban	1.24[a]
Selected Method—			USEtox™ 2.11

a – Designates an interim characterization factor.

A.12 Ecotoxicity Potential

Ecotoxicity is a measure of the effect of toxic substances on ecosystems. The effects on freshwater ecosystems are used as a proxy for general ecological impact. Characterization factors within the ecotoxicity model are based on fate, exposure, and effect factors. Each chemical included in the method travels multiple pathways through the environment. As a result of these pathways, various compartments (e.g., freshwater, terrestrial) and the species they contain will have differing opportunities to interact with the chemical in question (exposure). The effect factor refers to the potential negative consequences on ecosystem health when exposure does occur (Huijbregts, 2010). The exclusion of more localized parameters is justified in that it was found during the harmonization process that these parameters have a far lower impact on results than do the substances themselves. Ecotoxicity impacts are measured in terms of the Potentially Affected Fraction of species due to a change in concentration of toxic chemicals (PAF m^3.day/kg). These units are also known as comparative toxicity units (CTUe).

Global midpoint characterization factors are employed from the most recent version of USEtox™ available in OpenLCA, version 2.02. An updated version of USEtox™, version 2.11, was released in April 2019. Characterization factors for the heavy metals, toxic organics and DBPs were updated in the OpenLCA USEtox™ LCIA method to match version 2.11. All other characterization factors remain at the default value for OpenLCA's USEtox version 2 (recommended+interim) database. Not all heavy metals, toxic organics and DBPs have established characterization factors in the USEtox™ method. Several additional sources were used to identify appropriate characterization factors. When no appropriate characterization factor was identified, the pollutant was assigned a characterization factor equal to the median characterization factor for its trace pollutant group. For illustration purposes, Table A-12 lists some of the main chemicals found to contribute to ecotoxicity impacts (Ryberg, 2013) and their USEtox™ global characterization factors.

As is discussed in Section A.10, uncertainty in USEtox factors can range across one to three orders of magnitude for interim characterization factors, which are identified in Table

A-12. At the current time, all characterization factors for metal compounds are considered interim. Appropriate interpretation of results must consider the uncertainty associated with the use of interim characterization factors.

Table A-12. Main Pollutants Contributing to Ecotoxicity Potential Impacts (CTUe [PAF m^3.day/kg Pollutant]).

Pollutant	Chemical Formula	Compartment	Characterization Factor
Zinc, ion	Zn^{2+}	Ground water	1.3E+5[a]
Chromium VI	Cr(VI)	Ground water	1.0E+5[a]
Nickel, ion	Ni^{2+}	Ground water	3.0E+5[a]
Chromium VI	Cr(VI)	River	1.0E+5[a]
Arsenic, ion	As^{3+}	Ground water	1.5E+4[a]
Selected Method—			USEtox™ within TRACI 2.11

a – Designates an interim characterization factor.

APPENDIX B
LIFE CYCLE INVENTORY DATA

Appendix B – Life Cycle Inventory Data

B.1 Life Cycle Inventory Data Tables

Table B-1. Life cycle inventory data for unit processes that are consistent across scenarios

Process Name	Input Name	Mean Value	Min	Max	Units[2]	Distribution Type	Geometric Standard Deviation	Uncertainty Range Note
Core Facility	Electricity, grid	0.73	NA	NA	kWh/m^3	None	NA	Mean value: facility data
	Diesel, combusted	6.4E-3	NA	NA	liters/m^3	None	NA	Mean value: facility data
	Lime	3.5E-3	1.8E-3	5.3E-3	kg/m^3	Triangular	NA	Min, max and mean are based on 25%, 50% and 75% of 2020 lime consumption for which demand is expected to reduce following plant upgrades.
Preliminary Treatment – Screening and Grit Removal	Residuals to landfill	0.04	9.8E-3	0.11	kg/m^3	Triangular	NA	Mean value is based on facility data. Min and max values are based on survey data from eight U.S. WWTPs (U.S. EPA, 2003)
Secondary Treatment - Biological	Methane, to air	8.0E-3	NA	NA	kg CH_4/m^3	Lognormal[1]	1.69	See Appendix Section B.2 for details on process GHG emission estimation.
	Nitrous oxide, to air	4.4E-4	NA	NA	kg N_2O/m^3	Lognormal[1]	1.69	
Tertiary Treatment - Disk Filtration	Filter pads, polyester	5.6E-4	3.1E-4	8.2E-4	kg/m^3	Triangular	NA	Facility replaced 560 filter pads in 2020. Mean, min and max values based on total estimated mass of 3788, 2104 and 5471 kg.
	Filter nozzles, steel	1.5E-6	1.1E-6	1.9E-6	kg/m^3	Triangular	NA	Facility replaced 200 filter nozzles in 2020. Mean, min and max values based on total estimated mass of 10, 7.5 and 12.5 kg.
	Citric Acid	7.4E-5	6.6E-5	8.1E-5	kg/m^3	Triangular	NA	No data provided. Use microfilter quantities as proxy.
	Sodium hypochlorite	5.1E-5	4.6E-5	5.6E-5	kg/m^3	Triangular	NA	Mean value is based on facility data assuming a sodium hypochlorite density of 1209 kg/m^3. Min and max values estimated assuming +/- 10% of reported value.
Disinfection - Ultraviolet	Phosphoric Acid	3.4E-4	3.0E-4	3.7E-4	kg/m^3	Triangular	NA	Facility used 385 gallons in 2020. Assumed density of 1834 kg/m^3. Min and max values

Process Name	Input Name	Mean Value	Min	Max	Units[2]	Distribution Type	Geometric Standard Deviation	Uncertainty Range Note
								estimated assuming +/- 10% of reported value.
Sludge - Dissolved Air Flotation	Polymer	1.2E-3	9.5E-4	1.4E-3	kg/m^3	Triangular	NA	Facility used 10,230 gallons of polymer in 2020. Assumed 50% used in DAF and 50% used in belt filter press. Mass of polyacrylamide estimated assuming a polymer density of 8.6 pounds per gallon with an active polymer concentration of 40% w/w. Min and max values estimated as a function of +/- 10% baseline consumption, density range of 8.5-8.7 lbs/gallon and active polymer concentration range of 36-43%.
Sludge – Belt Filter Press	Polymer	1.2E-3	9.5E-4	1.4E-3	kg/m^3	Triangular	NA	
Sludge – Anaerobic Digestion	Methane, to air	2.8E-3	1.5E-3	7.9E-3	kg CH_4/m^3	Triangular	NA	Mean, min and max annual biogas production estimated based on mean, 25th and 75th percentile values of daily production for 2020. Mean, min and max estimates of fugitive methane leakage based on biogas methane content, leakage rate and biogas production. Daily production: 230,114 (223,835-238,875) standard cubic feet Methane content: 59% v/v (55%-64%) Leakage rate: 2% (1.2%-5%)
	Biogas (output)	0.35	NA	NA	m^3/m^3	None	NA	Allocation of biogas to combustion processes is described in Table 2-3. The effect of changes in biogas output on model results is assessed in the sensitivity assessment.
	Electricity (output)	0.63	0.61	0.65	kWh/m^3	Triangular	NA	Allocation of biogas to combustion processes is described in Table 2-3. Heat content of produced biogas is estimated assuming an LHV of 597 BTU/scf. Mean electrical and thermal efficiencies of the CHP system are 35% and 45%, respectively. In the best guess model run
	Heat (output)	0.07	0.06	0.07	m^3/m^3	Triangular	NA	

Process Name	Input Name	Mean Value	Min	Max	Units[2]	Distribution Type	Geometric Standard Deviation	Uncertainty Range Note
								(all scenarios), 54% of CHP heat production is utilized onsite, avoiding natural gas consumption. Min/max values for avoided energy consumption are estimated as a function of the share of biogas combusted in the CHP and boiler, CHP electrical efficiency (30-40%), CHP total efficiency (75-85%), boiler thermal efficiency (80-97%) and biogas LHV (556-649 BTU/scf).
Biogas - Flaring	Nitrogen oxides, to air	2.1E-4	1.9E-4	2.3E-4	kg/m^3 biogas combusted	Triangular	NA	Emission factors for these air pollutants was drawn from Paseo Real's air permit application. Min and max values estimated assuming +/- 10% of reported value.
	Carbon monoxide, to air	7.9E-4	7.1E-4	8.7E-4	kg/m^3 biogas combusted	Triangular	NA	
	VOCs, to air	5.2E-5	4.6E-5	5.7E-5	kg/m^3 biogas combusted	Triangular	NA	
	Sulfur dioxide, to air	1.3E-3	1.1E-3	1.4E-3	kg/m^3 biogas combusted	Triangular	NA	Mean values were pulled from Morelli et al. (2019). Min and max values estimated assuming +/- 10% of reported value.
	Particulate matter, to air	5.8E-4	5.2E-4	6.4E-4	kg/m^3 biogas combusted	Triangular	NA	
	Methane, to air	3.9E-3	3.5E-3	4.3E-3	kg/m^3 biogas combusted	Triangular	NA	
Biogas - CHP	Nitrogen oxides, to air	4.6E-3	3.0E-3	6.1E-3	kg/m^3 biogas combusted	Triangular	NA	Emission factors for these air pollutants was drawn from Paseo Real's air permit application. Min and max values estimated assuming +/- 10% of reported value.
	Carbon monoxide, to air	1.1E-2	7.6E-3	1.5E-2	kg/m^3 biogas combusted	Triangular	NA	
	VOCs, to air	2.6E-3	2.1E-3	3.0E-3	kg/m^3 biogas combusted	Triangular	NA	
	Sulfur dioxide, to air	1.4E-5	1.3E-5	1.5E-5	kg/m^3 biogas combusted	Triangular	NA	Mean values were pulled from Morelli et al. (2019). Min and max values estimated assuming +/- 10% of reported value.
	Particulate matter, to air	3.4E-5	3.1E-5	3.8E-5	kg/m^3 biogas combusted	Triangular	NA	
	Ammonia, to air	6.4E-5	5.8E-5	7.0E-5	kg/m^3 biogas combusted	Triangular	NA	

Process Name	**Input Name**	**Mean Value**	**Min**	**Max**	**Units[2]**	**Distribution Type**	**Geometric Standard Deviation**	**Uncertainty Range Note**
	Methane, to air	4.3E-3	3.9E-3	4.7E-3	kg/m^3 biogas combusted	Triangular	NA	
	Nitrous oxide, to air	1.0E-4	9.2E-5	1.1E-4	kg/m^3 biogas combusted	Triangular	NA	
Biogas - Boilers	Nitrogen oxides, to air	2.1E-4	1.9E-4	2.3E-4	kg/m^3 biogas combusted	Triangular	NA	Emission factors for these air pollutants was drawn from Paseo Real's air permit application. Min and max values estimated assuming +/- 10% of reported value.
	Carbon monoxide, to air	7.9E-4	7.1E-4	8.7E-4	kg/m^3 biogas combusted	Triangular	NA	
	VOCs, to air	5.2E-5	4.6E-5	5.7E-5	kg/m^3 biogas combusted	Triangular	NA	
	Sulfur dioxide, to air	5.2E-4	4.6E-4	5.7E-4	kg/m^3 biogas combusted	Triangular	NA	Mean values were pulled from Morelli et al. (2019). Min and max values estimated assuming +/- 10% of reported value.
	Particulate matter, to air	1.2E-4	1.1E-4	1.3E-4	kg/m^3 biogas combusted	Triangular	NA	
	Methane, to air	4.1E-5	3.7E-5	4.5E-5	kg/m^3 biogas combusted	Triangular	NA	
	Nitrous oxide, to air	1.0E-5	9.2E-6	1.1E-5	kg/m^3 biogas combusted	Triangular	NA	
Sludge - Composting	Electricity	0.05	NA	NA	kWh/digestate	None	NA	The facility reports use of 239,485 kWh in 2020 at their compost facility. Value was scaled up to 399,142 kWh to reflect future increase in volume of digestate composted.
	Natural Gas	9.8E-4	NA	NA	m^3/digestate	None	NA	The facility reports using 277 Dekatherms of natural gas in 2020. Assume this value reflects building heat and will remain constant when increasing quantity of digestate composted.
	Methane, to air	6.0E-4	NA	NA	kg CH_4/digestate	Lognormal[1]	1.69	Mean estimate is based on a methane emission factor of 8.2E-3 kg CH_4-C/kg C in compost feedstock. See supporting Excel workbook for sources.
	Carbon monoxide, to air	5.1E-5	NA	NA	kg CO/digestate	Lognormal[1]	1.69	Mean estimate is based on a CO emission factor of 4E-4 kg CO-C/kg C in compost feedstock (Hellebrand, 1998)

Process Name	Input Name	Mean Value	Min	Max	Units[2]	Distribution Type	Geometric Standard Deviation	Uncertainty Range Note
	Nitrous oxide, to air	1.6E-4	NA	NA	kg N_2O/digestate	Lognormal[1]	1.69	Mean estimate is based on a N2O emission factor of 0.0129 kg N_2O-N/kg N in compost feedstock. See supporting Excel workbook for sources.
	Ammonia, to air	4.1E-4	NA	NA	kg NH_3/digestate	Lognormal[1]	1.69	Mean estimate is based on a NH3 emission factor of 0.044 kg NH_3-N/kg N in compost feedstock (Hellebrand 1998)
	NMVOC, to air	1.0E-4	NA	NA	kg NMVOC/digestate	Lognormal[1]	1.69	Mean estimate is based on a NMVOC emission factor of 1.04E-4 kg NMVOC/kg compost feedstock. (Maulini-Duran et al., 2013)
Sludge - Land Application	Ammonia, to air	7.5E-5	NA	NA	kg NH_3/compost	Lognormal[1]	1.69	Mean estimate is based on NH_3 emission factor of 0.016 kg NH_3-N/kg NH_3-N in compost (Boldrin et al., 2011).
	Carbon sequestration	0.10	0.08	0.13	kg CO_2/compost	Triangular	NA	Mean estimate is based on the assumption that 12% of land-applied carbon is sequestered beyond 100 years (Boldrin et al., 2009; Yoshida et al., 2012)
	Nitrate, groundwater	0.03	NA	NA	kg NO_3/compost	Lognormal[1]	1.69	Mean estimate is based on a NO_3 emission factor (groundwater) of 0.2 kg NO_3-N/kg N in compost (Boldrin et al., 2011).
	Nitrate, surface water	0.03	NA	NA	kg NO_3/compost	Lognormal[1]	1.69	Mean estimate is based on a NO_3 emission factor (surface water) of 0.2 kg NO_3-N/kg N in compost (Boldrin et al., 2011).
	Nitrous oxide	7.0E-4	NA	NA	kg N_2O/compost	Lognormal[1]	1.69	Mean estimate is based on a N_2O emission factor of 0.015 kg N_2O-N/kg N in compost (Boldrin et al., 2011).
	Phosphorus, groundwater	6.6E-5	NA	NA	kg P/compost	Lognormal[1]	1.69	Mean estimate is based on a P (groundwater) emission factor of 0.005 kg P/kg P in compost, which was calculated based on method in (Nemecek and Kägi, 2007) using standard application rates.
	Phosphorus, surface water	1.8E-3	NA	NA	kg P/compost	Lognormal[1]	1.69	Mean estimate is based on a P (surface water) emission factor of 0.133 kg P/kg P in compost, which was calculated based on

Process Name	Input Name	Mean Value	Min	Max	Units[2]	Distribution Type	Geometric Standard Deviation	Uncertainty Range Note
								method in (Nemecek and Kägi, 2007) using standard application rates.
	Fertilizer, Nitrogen	0.02	0.01	0.03	kg Urea/compost	Triangular	NA	The mean quantity of avoided urea was estimated based on the nitrogen content of compost assuming that 30% of nitrogen is displaces production of chemical fertilizer. Min and max values are estimated using 20% and 40% substitution rates, respectively.
	Fertilizer, Phosphorus	0.11	0.07	0.14	kg SSP/compost	Triangular	NA	The mean quantity of avoided single super phosphate was estimated based on the phosphorus content of compost assuming that 73% of phosphorus displaces production of chemical fertilizer. Min and max values are estimated using 46% and 100% substitution rates, respectively.
	Fertilizer, Potassium	0.01	7.6E-3	0.01	kg K_2SO_4/compost	Triangular	NA	The mean quantity of avoided K_2SO_4 was estimated based on the potassium content of compost assuming that 60% of potassium displaces production of chemical fertilizer. Min and max values are estimated using 60% and 100% substitution rates, respectively.
Sludge - Landfilling	Diesel, combusted	3.4E-3	NA	NA	Liters/m^3	None	NA	NA
	LFG Flaring	0.02	0.01	0.03	m^3 biogas/m^3	Triangular	NA	Base value is based on first order decay of digestate in the landfill according to parameters in Table 2-8. Min value is based on DOCf of 0.5. Max value is based on DOCf of 0.8 and a decay factor of 0.2.
	Carbon sequestered	0.08	0.04	0.09	kg CO_2/m^3	Triangular	NA	Base value is based on first order decay of digestate in the landfill according to parameters in Table 2-8. Min value is based on DOCf of 0.8 and a decay factor of 0.2. Max value is based on DOCf of 0.5.

Process Name	Input Name	Mean Value	Min	Max	Units[2]	Distribution Type	Geometric Standard Deviation	Uncertainty Range Note
	Methane	4.2E-3	3.2E-3	6.0E-3	kg CH_4/m^3	Triangular	NA	Base value is based on first order decay of digestate in the landfill according to parameters in Table 2-8. Min value is based on DOCf of 0.5. Max value is based on DOCf of 0.8 and a decay factor of 0.2.
	Nitrous oxide	1.5E-4	NA	NA	kg N_2O/m^3	Lognormal[1]	1.69	Mean estimate is based on a N2O emission factor of 0.016 kg N_2O-N/kg N in landfilled digestate (Borjesson and Svensson, 1997).
Landfill Leachate Treatment	Electricity	0.56	NA	NA	kWh/m^3 leachate	None	NA	LCI data extracted from (Righi et al., 2013). Uncertainty not assessed.
	Oxygen	0.03	NA	NA	kg/m^3 leachate	None	NA	
	Alum	0.02	NA	NA	kg/m^3 leachate	None	NA	
	Sodium hydroxide	2.0E-3	NA	NA	kg/m^3 leachate	None	NA	
	Chloride, to water	0.10	NA	NA	kg/m^3 leachate	None	NA	
	COD, to water	0.04	NA	NA	kg/m^3 leachate	None	NA	
	Nitrogen, to water	0.01	NA	NA	kg/m^3 leachate	None	NA	
	Ammonium, to water	3.0E-3	NA	NA	kg/m^3 leachate	None	NA	
WWTP Effluent - Partial Diversion	Electricity	0.05	0.02	0.10	kWh/m^3	Triangular	NA	Electricity data provided by Carollo Engineering. Base, min and max values estimated assuming 1, 0.5 and 2 MGD of wastewater diverted to Rio Grande, respectively.

[1] Geometric standard deviation assigned based on recommended value from the Ecoinvent data quality pedigree matrix for a 'qualified estimate.' (Ciroth et al., 2012)

[2] '$/m^3$' notation in the unit denominator indicates that inventory data is normalized on the basis of 1 m^3 of treated wastewater.

[3] Disk filtration is only included for Baseline and Scenario 1.

Table B-2. Life cycle inventory data for unit process data specific to Scenario 1 – Sidestream Treatment

Input Name	Original Unit Process Name	Mean Value	Min	Max	Units[2]	Distribution Type	Geometric Standard Deviation	Uncertainty Range Note
Secondary Treatment - Biological	Methane, to air	8.0E-3	NA	NA	kg CH_4/m^3	Lognormal[1]	1.69	No change from baseline. See Appendix Section B.2 for details on process GHG emission estimation.
	Nitrous oxide, to air	4.0E-4	9.5E-5	7.4E-4	kg N_2O/m^3	Lognormal[1]	1.69	See Appendix Section B.2 for details on process GHG emission estimation.
Sidestream Treatment - Filtrate	Electricity	0.03	0.03	0.04	kWh/m^3	Triangular	NA	Electricity demand of the phosphorus and nitrogen sidestream processes is estimated to be 1,000 and 500 kWh/day, respectively. Min and max values estimated assuming +/- 10% of reported value.
	Magnesium Chloride	3.7E-3	3.3E-3	4.1E-3	kg active ingredient/ m^3	Triangular	NA	Estimated use is 100 gallons per day of 33% $MgCl_2$. Mass of active ingredient is estimated assuming a density of 1.32 g/cm^3. Min and max values estimated assuming +/- 10% of reported value.

[1] Geometric standard deviation assigned based on recommended value from the Ecoinvent data quality pedigree matrix for a 'qualified estimate.' (Ciroth et al., 2012)

[2] '$/m^3$' notation in the unit denominator indicates that inventory data is normalized on the basis of 1 m^3 of treated wastewater.

Table B-3. Life cycle inventory data for unit process data specific to Scenario 2 – Tertiary Filters

Input Name	Original Unit Process Name	Mean Value	Min	Max	Units[1]	Distribution Type	Geometric Standard Deviation	Uncertainty Range Note
Tertiary Treatment - Deep Bed Media Filters	Electricity	0.04	0.04	0.05	kWh/m^3	Triangular	NA	Estimated use to run both filters at design capacity is 700,000 kWh/year. Scaled to average annual flow. Min and max values estimated assuming +/- 10% of reported value.
	Sand	4.0E-3	3.4E-3	4.2E-3	kg/m^3	Triangular	NA	The mass of sand required was estimated assuming a sand volume of 6,250 ft^3 and a density of 1,522 kg/m^3. A density range of 1,281 - 1,602 kg/m^3 was used to estimate min/max values. Media lifespan = 20 years.
	Anthracite	2.1E-3	1.9E-3	2.3E-3	kg/m^3	Triangular	NA	The mass of anthracite required was estimated assuming an anthracite volume of 6,250 ft^3 and a density of 50 lb/ft^3. Min and max values estimated assuming +/- 10% of base value. Media lifespan = 20 years.
	Gravel	1.7E-3	1.5E-3	1.9E-3	kg/m^3	Triangular	NA	The mass of gravel required was estimated assuming a gravel volume of 2,500 ft^3 and a density of 1,602 kg/m^3. Min and max values estimated assuming +/- 10% of base value. Media lifespan = 20 years.
	Methanol	7.0E-3	6.0E-3	8.0E-3	kg/m^3	Triangular	NA	Methanol demand is 3.5 lbs methanol/lb Nitrogen removed. The quantity of nitrogen removed was calculated based on difference in reported effluent quality between baseline and Scenario 2. Min/max values were calculated using a range of methanol demands of 3-4 lbs/lb Nitrogen.
	Alum	0.03	0.02	0.07	kg/m^3	Triangular	NA	The alum requirement was estimated based on removal of 0.95 mg P/L (base value) with a target molar ratio of 5 g Aluminum/g Phosphorus. The aluminum content of alum ($Al_2(SO_4)_3$) is 0.16 g/g. Min/max values were calculated based on the potential range of required phosphorus removal, 0.85-2.45 mg P/L.

[1] '/m^3' notation in the unit denominator indicates that inventory data is normalized on the basis of 1 m^3 of treated wastewater.

Table B-4. Life cycle inventory data for unit process data specific to Scenario 3 – Reverse Osmosis

Input Name	Original Unit Process Name	Mean Value	Min	Max	Units[1]	Distribution Type	Geometric Standard Deviation	Uncertainty Range Note
Tertiary Treatment - Microfiltration	Electricity	0.06	0.05	0.07	kWh/m^3	Triangular	NA	Electricity data provided by Carollo Engineering. Min and max values estimated assuming +/- 10% of base value.
	Sodium hypochlorite	1.0E-4	9.0E-5	1.1E-4	kg/m^3	Triangular	NA	Chemical use data provided by Carollo Engineering. Min and max values estimated assuming +/- 10% of base value.
	Caustic soda	6.6E-5	5.9E-5	7.2E-5	kg/m^3	Triangular	NA	
	Sulfuric Acid	1.1E-5	3.0E-6	1.2E-5	kg/m^3	Triangular	NA	Chemical use data provided by Carollo Engineering. Min and max values estimated using range of sulfuric acid concentrations 25%-98%.
	Citric acid	7.4E-5	6.6E-5	8.1E-5	kg/m^3	Triangular	NA	Chemical use data provided by Carollo Engineering. Min and max values estimated assuming +/- 10% of base value.
	Membrane, MF/RO	6.5E-5	4.1E-5	1.4E-4	kg/m^3	Triangular	NA	MF membrane material is modeled as polyvinylfluoride. The quantity of membrane material was estimated assuming installation of 123 (range: 82-247) membrane units with an average lifespan of 9 years. Each unit has a membrane area of 77 m^2. Membrane fiber specifications used in base, min and max calculations are as follows: pore diameter - 0.03 µm, outer diameter - 1.3E-3 m, inner diameter - 7.0E-4 m, circumference - 4.1E-3 m and a PVDF density of 1.8 g/cm^3 (range: 1.68-1.97).
Tertiary Treatment - Reverse Osmosis	Electricity	0.27	0.24	0.29	kWh/m^3	Triangular	NA	Electricity data provided by Carollo Engineering. Min and max values estimated assuming +/- 10% of base value.
	Membrane, MF/RO	2.6E-4	2.3E-4	2.9E-4	kg/m^3	Triangular	NA	RO membrane material is modeled as polyvinylfluoride. The quantity of membrane material was estimated assuming a 7 MGD flowrate to the RO unit at the facilities design flow of 12 MGD. Each RO membrane unit has a flowrate of 1.6 m^3/hr requiring 1,049 membrane units with a safety factor of 1.5. Membrane units have an average expected lifespan of 9 years.

Input Name	Original Unit Process Name	Mean Value	Min	Max	Units[1]	Distribution Type	Geometric Standard Deviation	Uncertainty Range Note
	Proprietary solution 1, citric acid	2.5E-4	1.8E-4	3.1E-4	kg/m³	Triangular	NA	Chemical use data provided by Carollo Engineering. No information is available on the composition of proprietary cleaning chemicals. Citric acid is used as a proxy data source in the LCA model. Min and max values estimated assuming +/- 25% of base value, due to uncertainty about chemical composition.
	Proprietary solution 2, citric acid	4.6E-5	3.5E-5	5.8E-5	kg/m³	Triangular	NA	
Chemical Post-Treatment	Carbon dioxide	0.01	0.01	0.02	kg/m³	Triangular	NA	Chemical use data provided by Carollo Engineering. Min and max values estimated assuming +/- 10% of base value.
	Caustic soda	0.01	0.01	0.02	kg/m³	Triangular	NA	
Brine – Underground Inject	Electricity	0.55	0.45	0.69	kWh/m³	Triangular	NA	Electricity consumption was estimated assuming a brine flowrate of 0.088 m³/sec with a required pump pressure and efficiency of 1300 psi and 75%, respectively. Min and max values estimated assuming a range in pump pressures of 1200-1400 psi and a range of pump efficiencies between 65 and 85%.
	Water, to ground	0.17	NA	NA	m³/m³	NA	NA	The volume of produced brine is estimated assuming a reject rate of 29%.

[1] '/m³' notation in the unit denominator indicates that inventory data is normalized on the basis of 1 m³ of treated wastewater.

Table B-5. Life cycle inventory data for unit process data specific to Scenario 4 – Full Effluent Diversion

Input Name	Original Unit Process Name	Mean Value	Min	Max	Units	Distribution Type	Geometric Standard Deviation	Uncertainty Range Note
WWTP Effluent - Full Diversion	Electricity	0.18	0.13	0.20	kWh/m^3	Triangular	NA	Electricity data provided by Carollo Engineering. Min and max values estimated based on the range in estimated baseline pumping.

B.2 Greenhouse Gas Analysis

This section details the calculations used to determine the process-level GHG emissions from the wastewater treatment and sludge handling stages, from the effluent, and from landfilled sludge.

B.2.1 Methane Emissions from Biological Treatment

The methodology for calculating CH_4 emissions associated with the wastewater treatment configurations evaluated as part of this study is generally based on the guidance provided in the IPCC Guidelines for national inventories. CH_4 emissions are estimated based on the amount of organic material (i.e., BOD) entering the unit operations that may exhibit anaerobic activity, an estimate of the theoretical maximum amount of methane that can be generated from the organic material (B_o), and a methane correction factor that reflects the ability of the treatment system to achieve that theoretical maximum. In general, the IPCC does not estimate CH_4 emissions from well managed centralized aerobic treatment systems. However, there is acknowledgement that some CH_4 can be emitted from pockets of anaerobic activity, and more recent research suggests that dissolved CH_4 in the influent wastewater to the treatment system is emitted when the wastewater is aerated. The PR WWTP includes an optional anoxic zone preceding the aerated oxidation ditches.

The methodological equation, adapted from (IPCC, 2006; RTI International, 2010), is:

$$CH_{4\ PROCESS} = BOD\ (mg/L) \times Flow\ (m^3/yr) \times 1x10^3\ L/m^3 \times 1x10^{-6}\ kg/mg \times B_o \times MCF$$

Equation B-1

where:

$CH_{4\ PROCESS}$	=	CH_4 emissions from wastewater treatment process (kg CH_4 /yr)
BOD	=	Concentration of BOD entering biological treatment process (mg/L)
Flow	=	Wastewater treatment flow entering biological treatment process (m^3/yr)
B_o	=	maximum CH_4 producing capacity, 0.6 kg CH_4/kg BOD (IPCC, 2006)
MCF	=	methane correction factor (fraction)

IPCC guidelines recommend an MCF of 0 for a well-managed aerobic treatment process with an uncertainty range of 0-0.1. Daelman et al. (2013)evaluated emissions associated with a municipal treatment plant with biological nutrient removal (specifically nitrification and denitrification), resulting in an MCF of 0.05, which was used for this study due the presence of an anoxic zone for nitrification and denitrification and the fact that this value falls in the middle of the recommended IPCC range. This calculation estimates that approximately 53 metric tons of methane may be released annually from the biological treatment process.

B.2.2 Nitrous Oxide Emissions from Biological Treatment

The methodology for calculating N_2O emissions associated with wastewater treatment is based on estimates of emissions reported in the literature. The guidance provided in the IPCC Guidelines for national inventories does not provide a sufficient basis to distinguish N_2O emissions from varying types of wastewater treatment configurations, particularly related to biological nutrient reduction. More recent research has highlighted the fact that emissions from these systems can be highly variable based on operational conditions, specific treatment configurations, and other factors (Chandran, 2012). For this analysis, the best available N_2O emission factor for the biological treatment plant at the PR WWTP is for a plug-flow activated sludge treatment process. The reported emission factors indicate that between 0.09% and 0.62% of TKN influent to the biological process will be released as N_2O. The average of minimum and maximum emission factors, 0.36% was used as the baseline value in this study with the full range of emission factors informing the uncertainty assessment.

The methodological equation is:

$$N_2O_{\text{PROCESS}} = \text{TKN (mg/L)} \times \text{Flow (m}^3\text{/yr)} \times 1\text{x}10^3\ \text{L/m}^3 \times 1\text{x}10^{-6}\ \text{kg/mg} \times \text{EF\%} \times 44/28$$

Equation B-2

where:

N_2O_{PROCESS}	=	N_2O emissions from wastewater treatment process (kg N_2O /yr)
TKN	=	Concentration of TKN entering biological treatment process (mg/L)
Flow	=	Wastewater treatment flow entering biological treatment process (m^3/yr)
EF%	=	average measured % of TKN emitted as N_2O, %
44/28	=	molecular weight conversion of N to N_2O

B.2.3 Methane Emissions due to Anaerobic Digestion

Fugitive methane emissions from the anaerobic digesters are estimated as a function of biogas production, biogas methane content, methane density and assumed biogas leakage. The facility reports biogas production of 230,114 standard cubic feet/day (2,380,000 m^3/yr). Methane content of the produced biogas averaged 59.1% for the period from March 2020 to July 2021. The calculation assumes a methane density of 0.0417 lb/ft^3 (0.668 kg/m^3) at normal temperature and pressure. Fugitive methane leakage rates assessed in the LCA literature range from 0% to 5% of produced biogas CH_4 (Levis and Barlaz, 2011; Woon et al., 2016) with most values falling in the range of 1-3% (Slorach et al., 2019; Yoshida et al., 2012). A value of 2% was selected as the base value of this study, while the uncertainty assessment reflects a range of fugitive methane leakage between 1.2% and 5%. The base calculation estimates that approximately 19 metric tons of methane will be released annually from the digesters (range of 10-53 metric tons).

B.2.4 Nitrous Oxide Emissions from Effluent Discharged to Receiving Waters

The methodology for calculating nitrous oxide emissions associated with effluent discharge is based on the guidance provided in the IPCC Guidelines for national inventories.

N_2O emissions from domestic wastewater (wastewater treatment) were estimated based on the amount of nitrogen discharged to aquatic environments from each system configuration, which accounts for nitrogen removed with sewage sludge.

$$N_2O_{EFFLUENT} = N_{EFFLUENT}\ (mg/L) \times Flow\ (m^3/yr) \times 1x10^3\ L/m^3 \times 1x10^{-6}\ kg/mg \times EF_3 \times 44/28 \quad \text{Equation B-3}$$

where:

$N_2O_{EFFLUENT}$	=	N_2O emissions from wastewater effluent discharged to aquatic environments (kg N_2O/yr)
$N_{EFFLUENT}$	=	N in wastewater discharged to receiving stream, mg/L
Flow	=	Effluent flow, m^3/yr
EF_3	=	Emission factor (0.005 kg N_2O -N/kg sewage-N produced)
44/28	=	Molecular weight ratio of N_2O to N_2

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APPENDIX C
LCIA RESULTS

Appendix C – LCIA Results

See the accompanying Excel file titled Appendix C – LCIA Results.

APPENDIX D
DATA QUALITY ASSESSMENT

Appendix D – Data Quality Assessment

D.1 Data Quality Indicators Matrix

Table D-1. Data Quality Indicators Matrix

Source	Unit Process(es)	Unit Process Data Quality Indicator (1-5)				
		Source Reliability	Completeness	Temporal Correlation	Geographical Correlation	Technological Correlation
Plant Data						
Carollo 2021	Sidestream Phosphorous Removal, Deep Bed Media Filters, Microfilter, Reverse Osmosis, Chemical Post Treatment, Diversion Energy Difference	2	1	1	1	1
Lemon 2021a	Diversion	1	1	1	1	1
Lemon 2021b	Diversion	1	1	1	1	1
Luna 2021a	Sidestream Nitrogen Removal, Deep Bed Media Filters	1	1	1	1	1
Polymer	Belt Filter Press	1	1	2	1	1
PR Air Permit	Flare, CHP, Dual-fuel Boilers	2	1	1	1	1
PR Compost Electricity	Composting	1	1	1	1	1
PR Flow Data	Influent	1	1	1	1	1
PR Headworks Electricity	Facility Total (Electricity)	1	1	2	1	1
PR Input Data	Facility Total (Lime, Diesel)	1	1	1	1	1
PR Metals Data	Effluent	1	1	1	1	1
PR Natural Gas	Composting	1	1	1	1	1
PR Nonpotable Electricity	Facility Total (Electricity)	1	1	1	1	1
PR Renewable Energy	Flare, CHP, Dual-fuel Boilers	1	1	1	1	1
PR Reuse Data	Water Reuse	1	1	1	1	1
PR SCADA Data	Biological Treatment	1	1	1	1	1
PR Solid Waste	Composting	1	1	2	1	1
PR Staff 2021	Facility Total (Lime)	1	1	1	1	1
PR Staff Email 2021a	Screenings and Grit	1	1	1	1	1
PR Staff Email 2021b	Composting	1	1	1	1	1

Source	Unit Process(es)	Unit Process Data Quality Indicator (1-5)				
		Source Reliability	**Completeness**	**Temporal Correlation**	**Geographical Correlation**	**Technological Correlation**
Literature						
Amlinger et al. 2008	Composting	1	1	4	3	1
Andreoli et al. 2007	Anaerobic Digestion	1	1	4	1	1
Bastian et al. 2011	CHP	1	1	3	2	1
Boldrin et al. 2009	Composting	1	1	4	3	2
Boldrin et al. 2011	Land Application	1	1	4	3	1
Bonton et al. 2012	Reverse Osmosis	1	1	3	3	1
Chandran 2012	Biological Treatment	1	1	3	1	1
DEUSA 2021	Sidestream Phosphorous Removal	1	1	1	2	1
Disk Filter	Disk Filter	1	1	1	2	2
Favoino and Hogg 2008	Composting	1	1	4	3	2
Filter Media (Anthracite)	Deep Bed Media Filters	1	1	3	2	2
Filter Media (Gravel)	Deep Bed Media Filters	1	1	3	2	2
Fukomoto et al. 2003	Composting	1	1	5	3	2
Gas Density	Anaerobic Digestion	1	1	5	1	1
González et al. 2020	Land Application	1	1	1	3	1
HDR 2016	Biological Treatment	1	1	2	1	1
Hellebrand 1998	Composting	1	1	5		1
Hellmann 1997	Composting	1	1	5	3	1
IPCC 2006	Biological Treatment	1	1	5	3	2
K2SO4 Properties	Land Application	2	5	1	1	1
Kaberline et al. 2017	Sidestream Nitrogen Removal	1	1	2	2	1
Keng et al. 2020	Composting	1	1	1	3	1
Khoshnevisan et al. 2018	Land Application	1	1	2	3	1
Maulini-Duran et al. 2013	Composting	1	1	3	3	1
Membrane Filters	Microfilter	1	1	4	1	1
Morelli et al. 2019	Composting, Land Application	1	1	1	1	1

Source	Unit Process(es)	Unit Process Data Quality Indicator (1-5)				
		Source Reliability	Completeness	Temporal Correlation	Geographical Correlation	Technological Correlation
Nemecek and Kägi 2007	Land Application	1	1	4	3	1
Nitto 2019	Reverse Osmosis	1	1	1	2	1
Nkoa et al. 2014	Anaerobic Digestion	1	1	3	3	1
O'Kelly 2005	Anaerobic Digestion	1	1	5	1	1
Phosphoric Acid	Disinfection (UV)	1	1	1	1	1
Razza et al. 2009	Composting	1	1	4	3	2
Richard 2014	Composting	1	1	3	1	1
ROU 2007	Composting	1	1	4	3	2
Saer et al. 2013	Composting	1	1	3	3	1
Salemdeeb et al. 2017	Land Application	1	1	2	3	1
Sulfuric Acid	Microfilter	1	1	3	1	1
SYLVIS 2011	Composting	1	1	4	3	1
Tiquia et al. 2002	Composting	1	1	5	2	1
U.S. EPA 2003	Screenings and Grit	1	1	5	2	1
Yoshida et al. 2012	Composting	1	1	3	2	1

APPENDIX E
DETERMINATION OF METALS REMOVAL PERFORMANCE

Appendix E – Determination of Metals Removal Performance

The metals removal performance of each treatment scenario was determined using a combination of historical water quality data and expected performance of upgraded treatment scenarios based on the performance of similar systems. Given the nature of the data and how they were used to compute removal rates, tables are not shown in text form here. Instead, the reader is referred to the Metals tab of the project LCI workbook.

Influent and effluent data were provided by the PR WWTP in a range of forms, including long term effluent concentrations as well as a series of 4 quarterly samples, where pairwise influent and effluent samples were taken. ERG use these monthly samples to determine historic metals removal performance, which was assumed (conservatively) to be representative of the Baseline Scenario. To calculate removal rates for the Baseline Scenario as well as Scenarios 1-3, the following rules/methods were used:

- Where an influent concentration was measured, but the effluent sample returned a non-detect, the effluent concentration was assumed to be one half of the minimum detection limit (MDL), where the MDL was based on EPA Method 200.8 for metals and 245.1 for mercury.
- Scenario 1 (Filtrate Treatment) uses an annamox-based process and struvite production to remove nutrients, neither of which target metals. ERG therefore assumed that the metals removal performance of S1 was the same as the Baseline Scenario,
- For Scenarios 2 (Tertiary Filters) and 3 (RO), performance of similar systems from U.S. EPA (2021) were used as surrogates for determination of the percent removal performance of individual metal species.
- Scenario 4 was assumed to perform the same as the Baseline Scenario.

APPENDIX F
PARAMETER SENSITIVITY RESULTS

Appendix F – Parameter Sensitivity Results

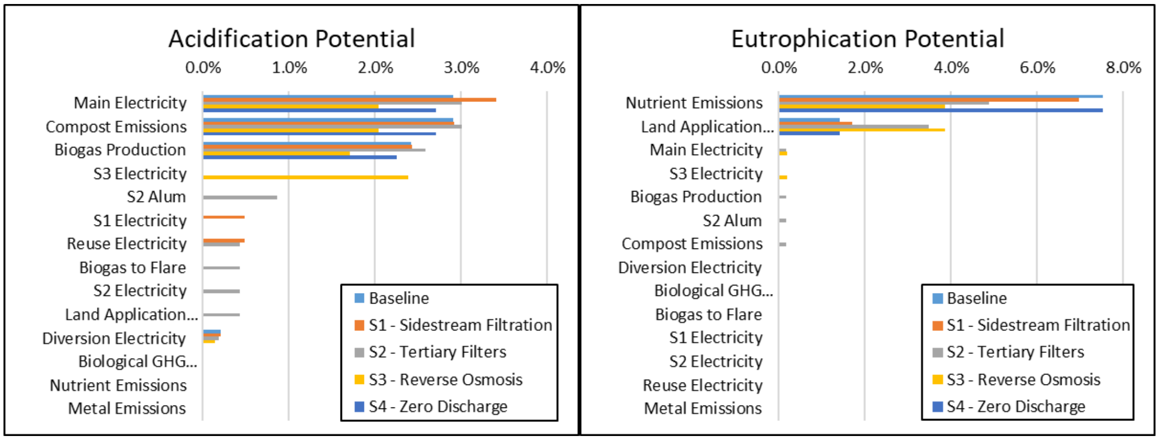

Figure F-1. Environmental metric (Acidification Potential and Eutrophication Potential) sensitivity to important model parameters. Axis values represent the percent change in baseline impact that results from a +/- 10% change in parameter values.

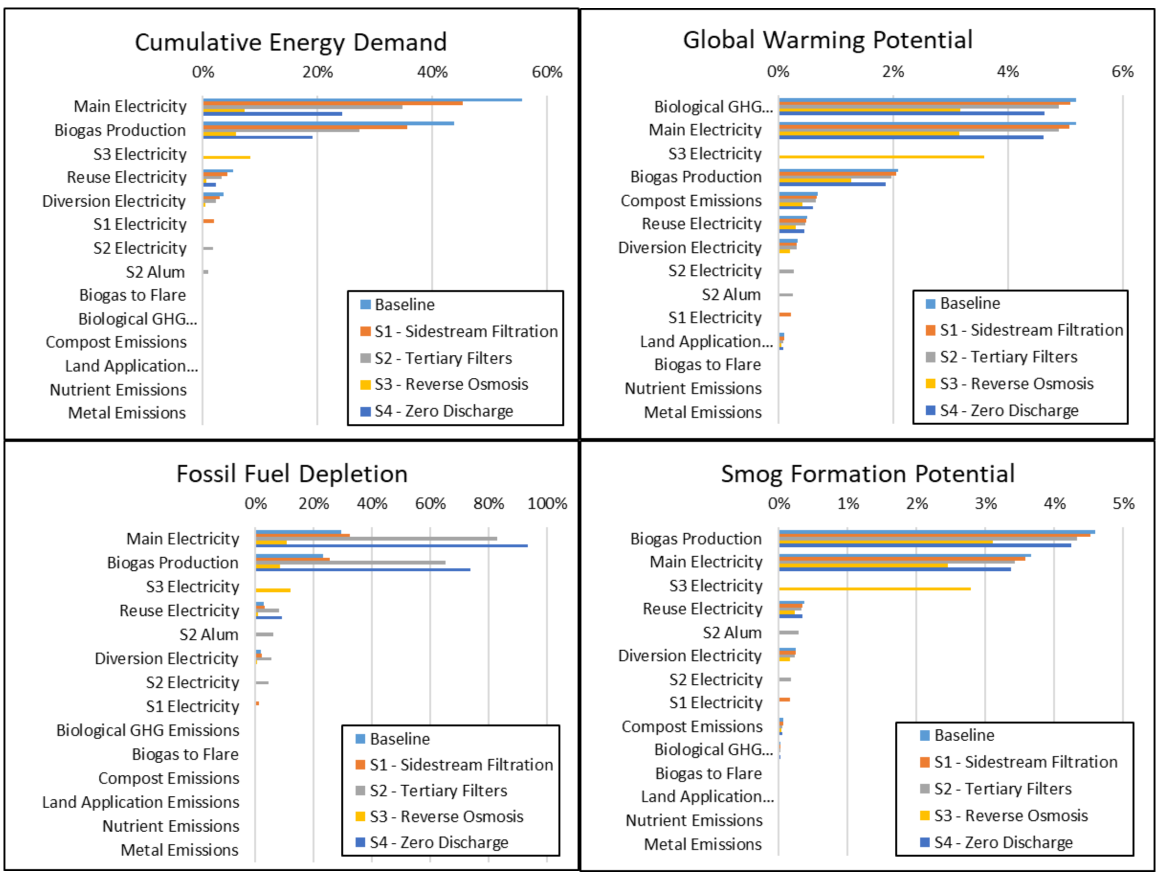

Figure F-2. Energy and Climate metric (Cumulative Energy Demand, Global Warming Potential, Fossil Fuel Depletion and Smog Formation Potential) sensitivity to important model parameters. Axis values represent the percent change in baseline impact that results from a +/- 10% change in parameter values.

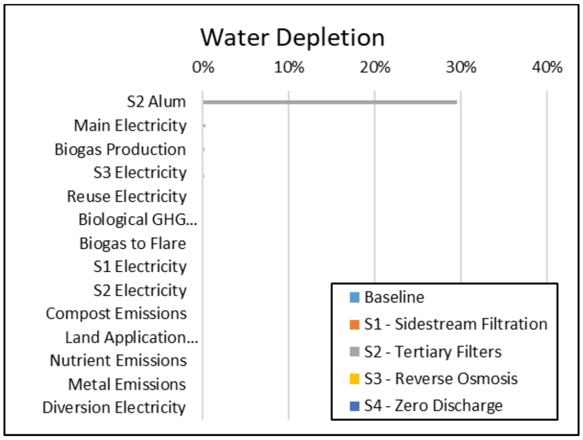

Figure F-3. Water metric (Water Depletion) sensitivity to important model parameter. Axis values represent the percent change in baseline impact that results from a +/- 10% change in parameter values.

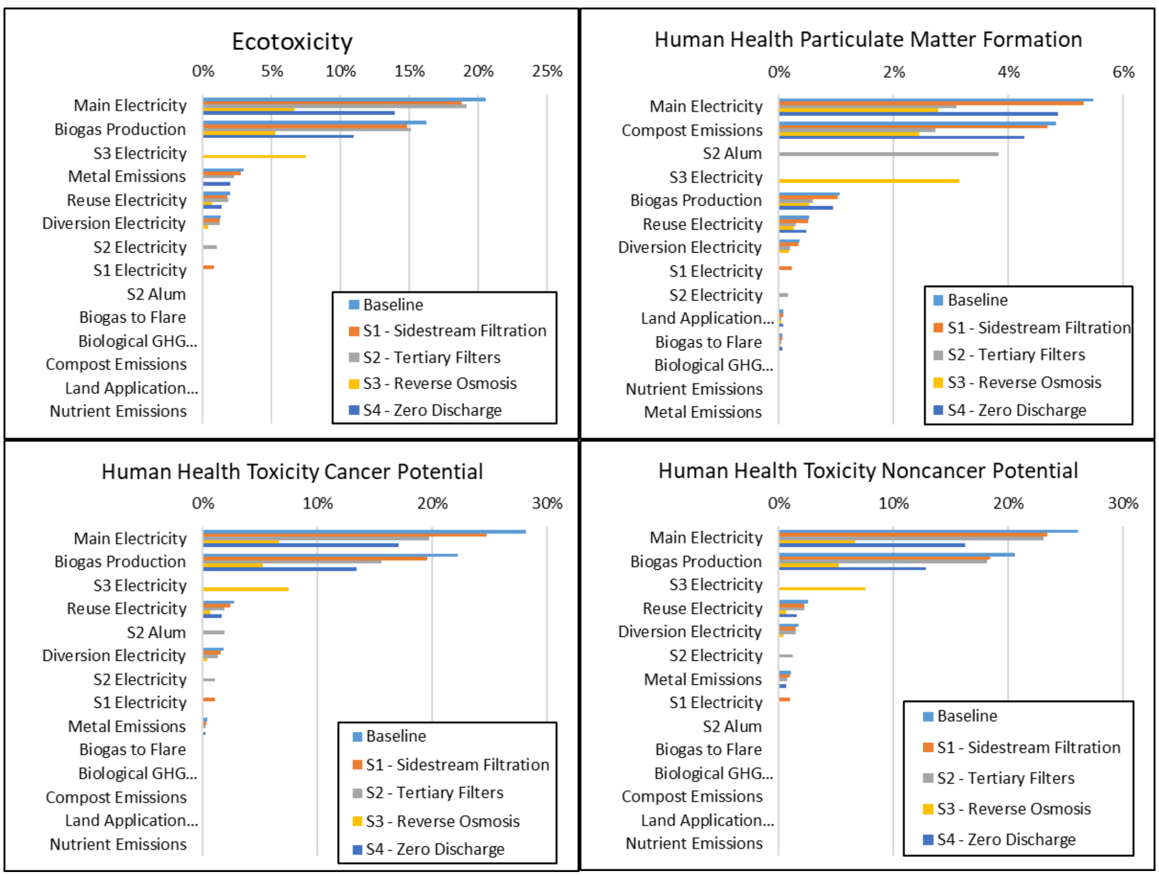

Figure F-4. Toxicity metric (Ecotoxicity, Human Health Particulate Matter Formation, Human Health Toxicity Cancer Potential, Human Health Toxicity Noncancer Potential) sensitivity to important model parameter. Axis values represent the percent change in baseline impact that results from a +/- 10% change in parameter values