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Vulnerability assessment index at process-level for the identification of adaptive strategies in wastewater treatment plants under climate change

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Abstract−Many studies have been conducted on climate change vulnerability assessments to develop adaptive strategies for climate change on a national or global scale. The development of an assessment tool for climate change on a process-level is necessary for evaluating vulnerability and to suggest an effective adaptive strategy in wastewater treatment plants (WWTP). Therefore, we proposed a vulnerability assessment index at the process-level in a WWTP to evaluate adaptive strategies for climate change in this study. The suggested process-level vulnerability assessment index is based on three performance WWTP indices: the effluent quality index (EQI), global warming potential (GWP), and operational cost index (OCI). Four different advanced WWTP processes were evaluated using the suggested vulnerability assessment index based on the A2 scenario, which is one of the carbon emission scenarios making predictions out to 2100 developed by the intergovernmental panel on climate change (IPCC). The adaptive strategies were evaluated at four conventional treatment processes to see the improvement of vulnerability of their processes, where the changes of their vulnerabilities are compared together. Suggested adaptive strategies in case studies showed that the process-level vulnerabilities were significantly decreased in the anaerobic/anoxic/aerobic (A_2O) and Virginia initiative project (VIP) processes, especially during the flood and winter seasons. Therefore, it is expected that the proposed vulnerability assessment index can be useful as a decision-supporting tool for selecting the appropriate adaptive strategy for each process.

Keywords: Climate Change Vulnerability Assessment, Effluent Quality Index (EQI), Greenhouse Gas (GHG), Operational Cost Index (OCI), Wastewater Treatment Process, Adaptive Strategy

INTRODUCTION

Climate change has an impact on the intensity and frequency of extreme events, such as typhoons, floods, and droughts, as well as a rise in the average temperature [1,2]. The damage due to climate change is a great concern since it provokes physical infrastructure destruction, an increase in mortality, and water supply difficulties, among others [3,4]. The IPCC has expressed that climate change is explicitly happening as a result of human activities and emphasizes the importance of greenhouse gas (GHG) mitigation to reduce the environmental problems of global importance caused mainly by industry [5]. Furthermore, the necessity of adaptive strategies is urgent to overcome the adverse effects of climate change produced by GHG [5]. Hence, there is a strong interest in the suggestion of adaptive strategies to climate change based on vulnerability assessment results, where vulnerability is defined by IPCC [5] as “the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes” [6]. Each system shows different degrees of climate change vulnerability, according to the system’s exposure to climate change and the surroundings where the system is currently present, namely the spatial area. This indicates that an appropriate adaptive strategy based on the system’s national and regional spatial characteristics is needed in order to suggest preventive measures for the adaptation of structures and processes to future atmospheric conditions.

Adaptive strategies of various infrastructures against climate change from the national to regional scale have been reported in recent studies. Several researchers have focused on methodologies of climate change vulnerability assessment as the first step to suggest proper adaptive strategies [1,7,8]. Brooks et al. [7] suggested a set of key vulnerability indicators at a national level with climate outcomes based on mortality by climate-related disasters. Myung et al. [1] spatially analyzed physical infrastructure’s climate exposure and assessed its vulnerability to climate change using a survey of professionals. Yoo et al. [8] developed a methodology to evaluate climate vulnerability in coastal cities under various climate stimuli at a regional scale, specifically for Busan, Korea. These studies on climate vulnerability assessment at the national and regional scales provided needed directions for economic support priorities for many cities and infrastructures [1,3,7]. However, t some water-related infrastructure upgrades might possibly be pushed back on the priority list because their potential to be damaged by climate change may be underestimated, although the vulnerability of water systems can hinder national development [1]. Although, it must be said that vulnerability assessments at the national or regional levels have been considered unsuitable for providing useful decision-making information for the development of adaptive strategies to combat climate

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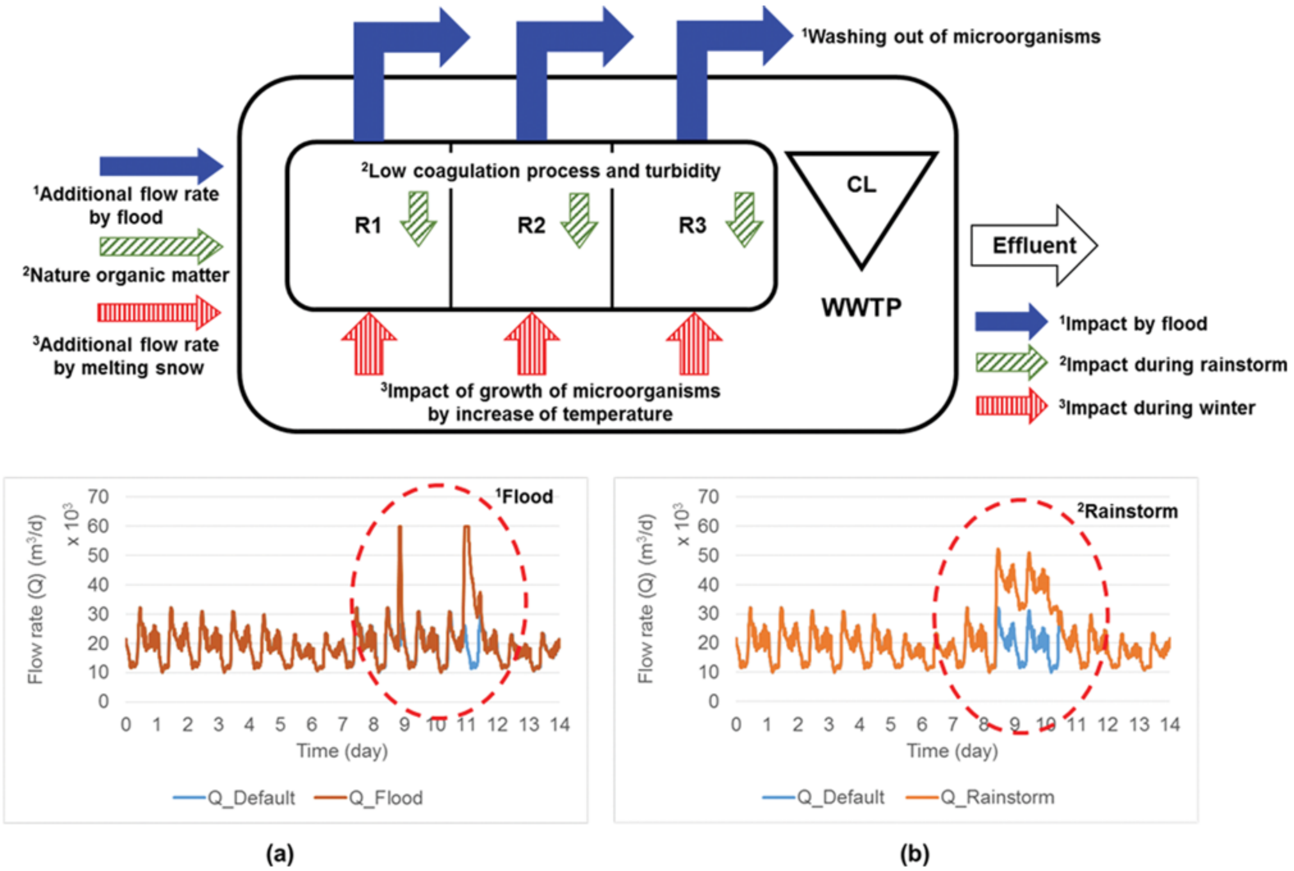

Fig. 1. The impact of climate change on WWTP in specific situations: (a) Variation of influent flow between default and floods and (b) Variation of influent flow between default and rainstorms [19].

change at the process level [1,7,9].

WWTP are important infrastructures that satisfy water demand for agriculture, industry, and households and are particularly vulnerable to hydrological variations (i.e., increase in flood/drought frequency) caused by climate change [3,4,10,11]. Fig. 1 shows the impacts of climate change on WWTP following a specific situation. In WWTP, floods lead to low effluent quality, which has the potential to cause eutrophication in the watershed by washing out the microorganisms responsible for treating nutrients. Rainstorms increase natural organic matter in influent that leads to low efficiency of the coagulation process and turbidity [12]. In addition, drought can exacerbate the influent quality in WWTP [13]. The increase in temperature caused by climate change has a significant effect on the growth of microorganisms as well as the flow rate into WWTP by melting snow, especially during the winter period [14]. Hence, an appropriate adaptive strategy for climate change should be developed to prevent damage in WWTP.

Only a few studies have anticipated the effects of climate change on water industries and have suggested adaptive strategies in the context of predicted climate scenarios. Thorne and Fenner [3] developed a simplified climate change impact assessment tool (SCIAT) to predict the potential risks of WWTP operation taking into consideration both climate and non-climate impacts, such as population growth in the future [3]. Langeveld et al. [15] implemented a data mining technique using observed data from WWTP under rainstorm conditions and varying temperatures to estimate the impact of climate variability on effluent [15]. Pielke [16] focused on the vulnerability of urban water infrastructures and suggested adaptive strategies to ameliorate climate change effects, especially in the United States [16]. The results of these studies provided meaningful vulnerability assessments at the process-level for operators to manage WWTP as a consequence of extreme events. However, most climate impact evaluations use a probabilistic model, including potential problems originating from any given system's special characteristics. Hence, the previous methodologies are difficult to implement for specific wastewater treatment processes and control strategies to reduce the adverse impacts of climate change on WWTP. For that reason, a new methodology was proposed based on a vulnerability index to assess the vulnerability of WWTP resulting from climate change and to suggest a proper adaptive strategy by considering the process by itself.

In this study, we suggest a vulnerability index at each process-level, which is evaluated at four processes and compared together. Effluent quality index (EQI), global warming potential (GWP), and operational cost index (OCI) were considered when developing the WWTP vulnerability index. The simplest adaptive strategy was proposed to reduce WWTP vulnerability to climate variability and an evaluation was carried out using the proposed vulnerability assessment index. The suggested vulnerability index is expected to provide an adaptation measure at the process level when

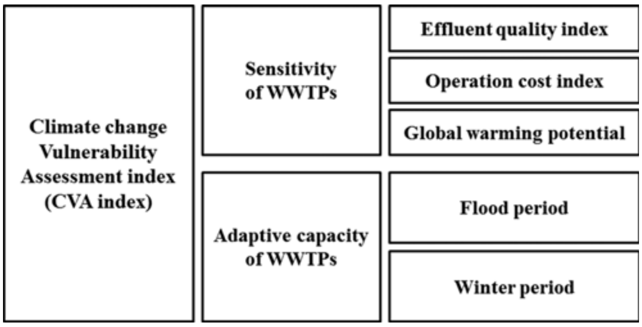

Fig. 2. Schematic diagram of climate change vulnerability assessment index.

constructing WWTP.

MATERIALS AND METHODS

1. WWTP Climate Change Vulnerability Assessment Index

Vulnerability is defined as a function of the character, magnitude, and rate of climate variation to which a system is exposed, considering its adaptive capacity (AC) and sensitivity [6]. To develop a new climate change vulnerability assessment index for WWTP, sensitivity and AC must be defined. Therefore, the climate change vulnerability assessment index (CVA index) for WWTP was developed in this study by combining the sensitivity and AC of WWTP as can be seen in Fig. 2. Sensitivity was defined as a function of effluent quality, operational cost, and the amount of GHG emissions widely used as performance indices. AC was defined as the time required to return effluent quality to under the legal limit after abnormal conditions caused by flooding and cold weather.

1-1. Sensitivity at WWTP

Based on the WWTP vulnerability index, sensitivity could be explained as the degree of response in a system given specific climate change conditions which include various effects. To develop an assessment index that includes specific effects on WWTP resulting from climate change, each performance evaluation index was standardized using the following reference method [1,6]:

$$SI_i=\frac{PEI_i-PEI_{ref}}{PEI_{ref}} \tag{1}$$

where SI is the sensitivity index at target year (i), PEI_i and PEI_{ref} are the performance evaluation indices at a target year and a reference year, respectively. In this study, EQI, OCI, and GWP were selected as performance evaluation indices for WWTP. The sensitivity indices for EQI, OCI, and GWP were expressed by SIE, SIO, and SIG, respectively. A high value of SI_i indicates that more degradation of process due to climate change impacts exists.

1-2. Adaptive Capacity at WWTP

AC is defined as the capacity to moderate harmful effects as well as to take advantage of climate change [6]. Although the regional scaled AC of WWTP incorporated economic support from the local government and environmental surroundings, only damage to the system due to an extreme event (e.g., flood) was considered as its AC for process-level vulnerability assessment [17]. For process-level vulnerability assessment, the AC index represented the amount of standards excess when the WWTP was operating during specific events (flood and winter). This can be estimated using the dimension index method as follows [18]:

$$\text{Adaptive capacity (AC)}=\frac{X-Min}{Max-Min} \tag{2}$$

where X is the number of days that the effluent exceeded the standards, and Max and Min are the maximum and minimum days that effluent exceeded the standard, respectively. In this study, ACs were estimated during floods (ACF) and the winter period (ACW). Floods and winter periods were assumed to occur from June to August and October to December, respectively. A high AC index value indicates that the process's capacity against climate change is small.

1-3. Calculation of Performance Evaluation Indices of WWTP for Sensitivity Indices

The EQI (kg pollution unit/day) averages the effluent load weight of contaminants that have a major influence on the receiving water quality over the period of observation [19]. It can be calculated by using Eq. (3) as follows:

$$EQI=\frac{1}{T\cdot 1000}\cdot\int_{t_i}^{t_k}\begin{pmatrix}\beta_{TSS}\cdot TSS_e(t)+\beta_{COD}\cdot COD_e(t)\\ +\beta_{TKN}\cdot S_{TKN,e}(t)+\beta_{NO_x}\cdot S_{NO_x,e}(t)\\ +\beta_{BOD5}\cdot BOD_{5,e}(t)+\beta_{TP}\cdot S_{TP,e}(t)\end{pmatrix}\cdot Q_e(t)\cdot dt \tag{3}$$

where T is the total evaluation period, t_k and t_i represent the start and end time of the period where the EQI is evaluated, β is the weighting factors for each pollutant in the effluent, TSS is the total suspended solid, COD is the chemical oxygen demand, TKN is the total Kjeldahl nitrogen, TN is the total nitrogen, BOD_5 is the biological oxygen demand, and TP is total phosphorus in which the subscript e denotes the effluent [20]. All concentrations are expressed in mg/L units. The weighting factors used in this study were: β_{TSS}=2, β_{COD}=1, β_{TKN}=30, β_{NO_x}=10, β_{BOD_5}=2, and β_{TP}=50 [21]. Where the values for β_{TKN} and β_{NO_x} were modified to consider the fact that ammonium is more injurious for the environment than nitrate or nitrite [34]. β_{TP} was also changed to stimulate the operational settings that caused higher bio-P removal [21]. Finally, Q_e represents the effluent flow rate (m^3/d).

The OCI is the combination of energy consumption and sludge treatment cost. It can be calculated using Eq. (4) as follows:

$$OCI=AE+PE+3\cdot SP+3\cdot EC=ME-6\cdot MP+\max(0, HE^{net}) \tag{4}$$

where AE is the aeration energy (kWh/d), PE is the pumping energy (kWh/d), and SP is the sludge production (kgTSS/d), EC represents the external carbon addition (kg COD/d), ME is the mixing energy (kWh/d), MP is methane production (kg CH_4/d), and HE^{net} stands for the net heating energy required to heat the sludge in the anaerobic digester [22]. The operational cost is used for roughly comparing target processes; however, there is no specific indicator for calculating operational cost in previous researches [32]. Therefore, only AE, PE, and SP were used to calculate OCI in this study, according with the equations used by Kim and Yoo [32].

The GWP is the relative measurement of how much heat is trapped in the atmosphere by GHG, which is defined by Equation.

GWP and GHG, such as CH_4, or N_2O, are expressed as a unit of carbon dioxide.

$$GWP=(E_{CO2}\times GWP_{CO2})+(E_{CH4}\times GWP_{CH4})+(E_{N2O}\times GWP_{N2O}) \quad [gCO_2e^-/day] \tag{5}$$

where E_{CO2}, E_{CH4}, and E_{N2O} correspond to the amount of emitted carbon dioxide, methane, and nitrous oxide from WWTP per day, respectively. GWP_{CO2}, GWP_{CH4}, and GWP_{N2O} are applied at 1, 25, and 298, respectively [23]. In this study, we only considered the direct effect of the main effluents of BOD, COD and N elements on GHG impact, but not phosphorous effect, where these components are the primary GHG of concern from the treatment system of infrastructures. Phosphorous's contribution on the GHG impact should be calculated on the amount of wasted sludge from the system boundary, where the GHG impact of the sludge containing phosphorous depends strongly on the types of sludge treatments.

The GHG emissions from WWTP were estimated based on mass balances of carbon and nitrogen since both elements are components of the primary GHG of concern from this infrastructures [24]. COD, BOD, and N balances are described as follows in Eqs. (6)-(9):

$$COD_i=COD_e+COD_w+COD_r \ [g/d] \tag{6}$$

$$BOD_i=BOD_e+BOD_w+BOD_r \ [g/d] \tag{7}$$

$$TKN_i+NO_X-N_i=TKN_e+NO_X-N_e+TKN_w+NO_X-N_w+TKN_r+NO_X-N_r \ [g/d] \tag{8}$$

$$TN=TKN+NO_X-N \ [g/d] \tag{9}$$

where subscripts i, e, w, and r are the influent, effluent, waste and removed carbon and nitrogen in (g/d), respectively, due to the degradation of organic matter in wastewater. The estimation of COD_r, BOD_r, and TN_r, and the CO_2, CH_4, and N_2O emissions from WWTP were calculated by using Eqs. (10)-(12) as follows [24-26]:

Table 1. The parameter values to estimate the amount of emitted GHGs from the WWTP

Parameters	Values	Units
Y_{CO2}^{an}	0.428	$gCO_2/gBOD$
Y_{CO2}^{de}	3.228	gCO_2/gN-nitrate
Y_{CO2}	0.49	$gCO_2/gBOD$
B_0	0.25	$gCH_4/gCOD$
MCF	0.8	-
GF	0.013	gN_2O/kgN

$$E_{CO2}=(Y_{CO2}^{an}\times BOD_r^{anaerobic})+(Y_{CO2}\times BOD_r^{aerobic})+(Y_{CO2}^{de}\times NO_X-N_r) \ [gCO_2/d] \tag{10}$$

$$E_{CH4}=B_0\times MCF\times COD_r \ [gCH_4/D] \tag{11}$$

$$E_{N2O}=GF\times TN_r \ [gN_2O/d] \tag{12}$$

where E_{CO2}, E_{CH4}, and E_{N2O} are the amount of CO_2, CH_4, and N_2O emitted from the WWTP, respectively. Y_{CO2}^{an}, Y_{CO2}^{de}, and Y_{CO2} are the yield of CO_2 in anaerobic, denitrification, and aerobic reactions, respectively. $BOD_r^{anaerobic}$ and $BOD_r^{aerobic}$ are the removed BOD mass in anaerobic and aerobic reactors, and NO_X-N_r represents the removed nitrate mass in WWTP. The values of parameters in Eqs. (10)-(12) are presented in Table 1.

2. Vulnerability Assessment of WWTP

The CVA index for WWTP was developed by combining the proposed sensitivity and AC indices as can be seen in the following Eq. (13):

$$\text{CVA index}=\frac{\alpha\times SIE+\beta\times SIO+\gamma\times SIG+0.5\times(ACF+ACW)}{2} \tag{13}$$

where α, β, and γ are weighting factors according to each sensitiv-

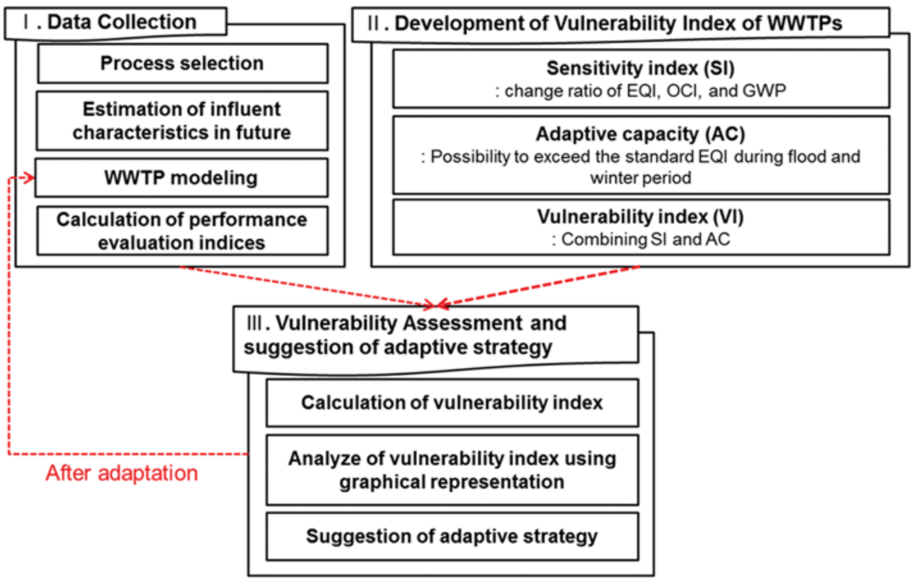

Fig. 3. Proposed scheme of a process-level vulnerability assessment index and validating potential use of the vulnerability index in WWTPs for climate change.

ity, and the total sum of the weighting factors has to be equal to 1. The weighting factors on the AC indices were determined to be 0.5 to balance the significance of each indicator, since the equal weighting factors of sensitivity and adaptive capacity cause overestimation of CVA index. Therefore, the sum of weighting factors of sensitivity is 1, and the weighting factors of adaptive capacity is determined as 0.5 for balancing importance [8]. EQI, OCI, and GWP were estimated by the information of target Korean WWTP processes such as physical and operational conditions. Adaptive capacities during floods from June to August and the winter period from October to December were calculated based on specific climate characteristics of Korea. It indicates that sensitivities of EQI, OCI, and GWP, and adaptive capacities during floods and the winter period had appropriate capability of Korean WWTP. The CVA therefore had ability to estimate Korean WWTP and the high value of CVA implied that WWTP are more sensitive and vulner-

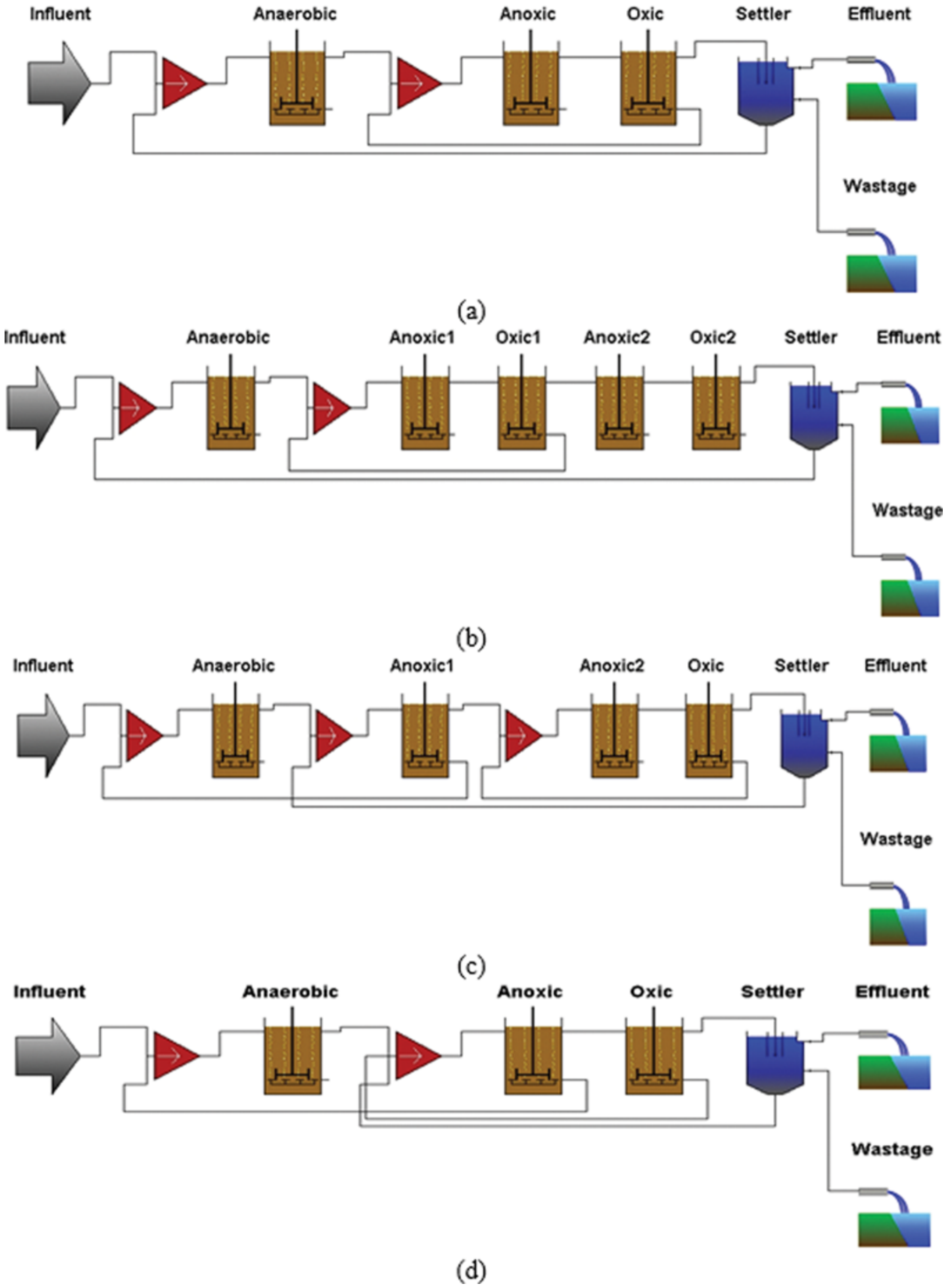

Fig. 4. Layout of four advanced wastewater treatment processes: (a) Anaerobic/anoxic/aerobic (A_2O), (b) BarDenPho, (c) MUCT, and (d) VIP process.

able to climate change.

The CVA index showed the WWTP state in process-level, but the implication of which part was dominant in its vulnerability needed to be explained. A radar graph was used to analyze the vulnerability assessment results for this purpose. Radar graphs are widely used to simultaneously represent multivariate observations in two dimensions. It is possible to evaluate overall WWTP vulnerability by comparing the area of each observation as well as simultaneously representing the relative contribution of each indicator to total vulnerability using a radar graph [27].

3. Proposed Methods

Fig. 3 shows the proposed framework for developing a process-level vulnerability assessment index and evaluating adaptive strategies in WWTP to respond to climate change. The proposed method largely consists of three sections: (1) data collection based on a future climate change scenario, (2) developing a vulnerability assessment index in WWTP, and (3) developing a vulnerability assessment for four major biological processes, and suggesting adaptive strategies.

3-1. Target Processes of the Vulnerability Assessment

Anaerobic/anoxic/aerobic (A2O), Barnard Denitrification Phosphate (BarDenPho), Modifed University of Cape Town (MUCT), and Virginia Initiative Project (VIP) were selected as the target processes to assess climate change vulnerability as presented in Fig. 4. Four WWTP processes were designed based on measured influent data from H-WWTP in 2010 and standard design guidelines for WWTP in Korea. H-WWTP, located in H-city, Gyeonggi-do, Korea, used Daewoo nutrient removal (DNR) process. It consisted of two anaerobic, an anoxic, and an oxic reactors. The DNR process was developed by Daewoo for improving nutrient removal efficiency and convenience of maintenance control of WWTP. It has characteristics of efficient nutrient removal ability under low temperature condition and prevention of additional emission of additional phosphorus in the anaerobic reactors. The designed physical and operational conditions in four major biological wastewater treatment processes are, respectively, shown in Tables 2 and 3.

The data required for assessing the vulnerability of target processes was obtained using GPS-X (Hydromantis Inc, Canada), which is a simulator based on mathematical models for biological processes (activated sludge models, ASMs) [28]. Among the ASMs, activated sludge model No. 2d (ASM2d) was selected to consider phosphorus and nitrogen removal in the WWTP processes.

3-2. Estimation of Inflow Characteristics to WWTP Based on Future Climate Change Scenarios

The A2 scenario projects possible GHG emissions based on

Table 2. Annual average influent conditions of H-WWTP in Korea

	Influent conditions
Flow rate (Q)	8,896 m^3/d
COD	200 g COD/m^3
BOD	87 g O_2/m^3
TSS	100 g/m^3
T-N	24 g N/m^3
T-P	2.8 g P/m^3
Temperature	16.5 °C

Table 3. Reactor sizes and operational conditions in A_2O, BarDenPho, VIP, and MUCT processes

		A_2O	BarDenPho	VIP	MUCT
Volume (m^3)	Anaerobic	750	750	1,500	1,500
	Anoxic1	1,250	4,500	3,000	4,000
	Oxic1	4,500	9,000	4,500	7,500
	Anoxic2		1,500		4,000
	Oxic2		450		
	Total	6,500	16,200	9,000	17,000
Waste sludge (m^3/d)		50	150	190	150
Recycling fraction (m^3/d)		0.3Q	1Q	1Q	1Q
Internal 1 (m^3/d)		2Q	4Q	2Q	2Q
Internal 2 (m^3/d)		-	-	2Q	2Q
Settler area (m^2/d)		500	500	500	500

*Q: influent flowrate

high population growth in the Special Report on Emissions Scenarios (SRES) and was applied to predict the impact of climate change on WWTP in the future [6]. Based on the A2 scenario, previous researchers have predicted an increase of 20% and 50% in the concentrations of total nitrogen and phosphorus in influent, respectively, as well as influent flow rate and temperature growth by 37% and 3.4 °C by 2100, respectively [10,29]. It was assumed that the annual average increments of pollutant concentration, flow rate, and influent temperature were constants from 2010 until 2100 and, therefore, the influent conditions could be estimated for 2020, 2050, and 2100.

3-3. Suggestion of an Adaptive Strategy at the Process-level for WWTP

Adaptive strategies were suggested to reduce the harmful effects of climate change for each process based on its assessed vulnerability. According to the influent scenarios, hydraulic retention time (HRT) might be reduced by an increase in the influent flow rate in WWTP. The increased influent flow rate, caused by climate change such as flood or rainstorm, directly decreases HRT. Moreover, the decreased HRT can cause microorganism washout and concentration of microorganism decrease. It results in degradation in the efficiency of pollutant removal in WWTP. Therefore, we suggested two kinds of adaptive strategies for adjusting the efficiency of WWTP based on relevant HRT. The first strategy was to change the operating conditions, and the second strategy was to increase the volume of anaerobic, anoxic, and aerobic reactors as adaptive strategies against climate change.

Table 4 presents three adaptive strategies for increasing the AC of WWTP. The first adaptive strategy for the operation portion (O.1) was implementation of a chemical precipitation process using alum after a flood. This strategy decreased the phosphorus concentration of the effluent after the flood. The O.2 strategy was implemented to increase the recycled fraction by three times during the winter. It led to an increase in the SRT in the WWTP process and caused the growth of microorganisms during winter. It prevented a decrease in WWTP efficiency caused by low temperature during winter. The O.3 strategy was a combination of the O.1 and O.2 strategies. The combination of both strategies was expected to

Table 4. Two main adaptive strategies in wastewater treatment plants

Strategy		Description	Purpose
Operation	O.1	Chemical precipitation using alum after flood	Phosphorus removal efficiency
	O.2	Increasing recycle fraction by 3 times during the winter season	Microorganism concentration
	O.3	Combination of O.1 and O.2	Nitrogen removal efficiency and microorganism concentration
Design	D.1	Increasing anaerobic reactor size twice	Phosphorus removal efficiency
	D.2	Increasing anoxic reactor size twice	Nitrogen removal efficiency
	D.3	Combination of D.1 and D.2	Phosphorus and nitrogen removal efficiency

Table 5. The multiplication factors for calculation of total operational cost

Cost factors	Multiplier
Effluent fines	50 €/EQI (EQI=kg/d)
Sludge treatment costs	75 €/SP (SP=kgTSS/d)
Energy costs	25 €/PE or AE (PE=AE=kWh/d)

Notes: EQI: Effluent quality index; SP: sludge production; PE: Pumping energy; AE: aeration energy

Table 6. Average value of three performance indices and two adaptive capacities for WWTP in 2010 as a reference year

	A_2O	BarDenPho	MUCT	VIP
EQI (kg/d)	2,369	2,190	2,008	2,301
OCI (1/d)	2,840	3,720	3,894	4,087
GWP (kg CO_2 e^-/d)	10,716	10,730	10,800	9,901
ACF	0.2857	0.2857	0.2843	0.2857
ACW	0	0	0	0.1271

increase microorganism concentration and phosphorus removal at each specific event. On the other hand, the D.1 strategy increased the anaerobic reactor volume twice. It led to more phosphorus being released from phosphorus accumulating microorganisms (PAO) provoking a larger driving force of luxury uptake in the aerobic reactor. As a result, the total removal efficiency of phosphorus could be enhanced. The objective of the D.2 strategy was to increase the anoxic reactor volume twice. It caused a more activated denitrification process, in which nitrogen removal efficiency was improved. The D.1 and D.2 strategies were combined to generate the D.3 strategy, which simultaneously increased both phosphorus and nitrogen removal efficiency. The adaptive strategies were compared with default scenarios (without considering adaptive strategies) according to the climate vulnerability assessment index and total cost index (TCI), which can be calculated using Eq. (14) as follows [30]:

$$\text{TCI}=(\text{Effluent fines}\times\text{EQI})+(\text{Sludge treatment costs}\times\text{SP})+(\text{Energy cost}\times(\text{PE}+\text{AE})) \tag{14}$$

The values of the parameters considered in Eq. (14) are summarized in Table 5.

RESULTS AND DISCUSSION

To estimate the CVA index of four wastewater treatment processes, AC and sensitivity were measured under climate change conditions. Sensitivity was assessed by comparing differences between WWTP performances in a target year and a reference year. AC was evaluated using the environmental impacts of the processes during floods and winter seasons, in which the CVA indices of each process were compared using a radar graph.

1. Performance Indices of WWTP in the Reference Year (2010)

Table 6 presents the values of the three performance indices, ACF, and ACW. In terms of effluent quality, A_2O showed the largest environmental load in an aquatic system, followed by VIP, BarDenPho, and MUCT. These results were related to the total reactor size of each process. In other words, MUCT had the largest reactor size of all of the processes, followed by the BarDenPho, VIP, and A_2O processes. In 2010, the EQI values of all of the processes were maintained under the EQI standard value (i.e., 3,907). On the other hand, the VIP process showed high values of OCI, because it produced large amounts of sludge. The MUCT was the largest producer among the four processes due to its enforced nitrogen removal process by adding anoxic and aerobic reactors. The MUCT could treat more nitrogenous pollutants than the other processes, but it produced more N_2O gas through incomplete nitrification and denitrification [25,31,40]. All of the processes showed relatively small values of the excess rate after the flood. This result indicates that all of the processes rapidly recovered their pollutant treating ability after the flood damage, although microorganisms were washed out of the WWTP by the flood. However, because the flow of the WWTP has large variations, effluent requirements will become more stringent. This can cause the need for installation of additional treatment facilities to comply the requirements [35].

2. Vulnerability Assessment of Four Target WWTP Processes

Fig. 5 and Table 7 present the results of a vulnerability assessment of four target WWTP processes with numerical and graphical representation. The SIE index of all of the processes increased during the simulation period. This was evidence that climate change produced adverse effects, decreasing pollution treatment efficiency in the processes. A_2O and VIP processes obtained high variation of SIE, since they were the smallest among the selected WWTP processes. SIO and SIG indices showed a small change in all of the processes. This result suggests that climate change did not produce an effect on the operational costs and GHG emissions. ACF

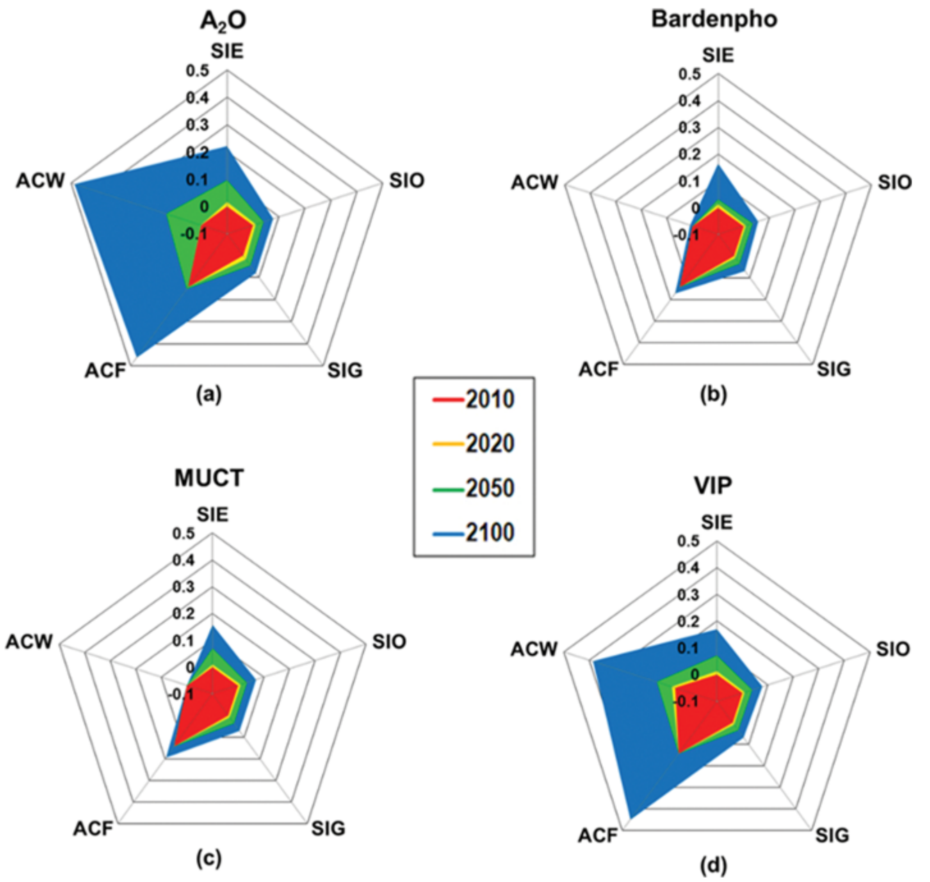

Fig. 5. Radar graphs of four different WWTP biological processes under A2 scenario: (a) A_2O, (b) BarDenPho, (c) MUCT, and (d) VIP process.

Table 7. SI, AC, and CVA index of four WWTP processes under A2 scenario

Process	Year	SIE	SIO	SIG	ACF	ACW	CVA
A_2O	2010	0.0000	0.0000	0.0000	0.2857	0.0000	0.0714
	2020	0.1010	0.0658	0.1245	0.2857	0.0025	0.1206
	2050	0.5768	0.2422	0.3021	0.3029	0.2690	0.3296
	2100	1.3297	0.4651	0.5284	0.9257	0.9760	0.8622
BarDenPho	2010	0.0000	0.0000	0.0000	0.2857	0.0000	0.0714
	2020	0.0821	0.0529	0.0521	0.2857	0.0000	0.1026
	2050	0.1862	0.2090	0.2090	0.2857	0.0000	0.1720
	2100	0.9897	0.3408	0.4120	0.3443	0.0197	0.3811
MUCT	2010	0.0000	0.0000	0.0000	0.2843	0.0000	0.0711
	2020	0.0618	0.0667	0.0517	0.2857	0.0000	0.1014
	2050	0.4219	0.2067	0.2141	0.2857	0.0000	0.2117
	2100	0.9475	0.4218	0.4253	0.3886	0.0000	0.3960
VIP	2010	0.0000	0.0000	0.0000	0.2857	0.1271	0.1032
	2020	0.0793	0.0556	0.0540	0.2857	0.1548	0.1416
	2050	0.4269	0.2277	0.2157	0.2857	0.2709	0.2841
	2100	1.0178	0.4700	0.4310	0.8900	0.7717	0.7349

and ACW explained the AC of WWTP processes during floods and winter seasons. In the results, all of the WWTP processes showed a similar variation in 2010 and 2020, but A_2O and VIP showed the highest variation in 2050 and 2100 among all of the WWTP processes. These results indicate that the A_2O and VIP processes ACs withstood specific conditions (flood, winter) that produce adverse effects on WWTP and were decreased by continued climate change. A similar result was obtained in a previous research where VIP process could not be maintained properly during extreme climate change conditions; therefore, it was identified as the most vulnerable because of its sensitivity [39]. Researchers have noted the importance of connect vulnerability with adaptation strategies in order to increase climate change AC [27,39]. Since A_2O and VIP processes showed a low AC to respond to continued climate change (A2 scenario), adaptive strategies were developed for both processes with the aim of create responses that could address changes at process level.

3. Climate Change Adaptive Strategies for A_2O and VIP Processes

To establish the climate change adaptive strategies for A_2O and VIP processes, which had the lowest AC of climate change, an investigation of fluctuations in the process conditions was needed. Fig. 6 presents variations in the A_2O and VIP processes as well as HRT, EQI, and microorganisms under the A2 scenario. HRT variations of two WWTP processes are presented in Figs. 6(a) and 6(b). The HRT of all of the reactors included in each process was decreased under the A2 scenario, and this could be connected to the decrease in the growth of the microorganisms. Figs. 6(d) and 6(e) present microorganism concentrations in A_2O and VIP processes based on ASM2d. Only heterotrophs showed the highest concentration in all of the periods with respect to other microorganisms that decreased under the A2 scenario. In addition, the nitrogen and phosphorus removal efficiency were decreased in A_2O and VIP processes. Finally, these situations could be confirmed by variation in the EQI under the A2 scenario (Fig. 6(c)). The same figure shows that the EQI values of 2100 exceeded the EQI standard of 2010. The standards for effluent pollutants are decreasing over time. Therefore, an adaptive strategy is necessary for better performance in the future [39].

Fig. 7 presents the results of adaptive strategies by changing operation conditions in A_2O and VIP processes by 2050 and 2100. Figs. S1 to S3 also present detailed information about operation adaptive strategies that include the T-P and T-N effluent concentrations, EQI variation, and microorganism concentrations. None of the adaptive strategies showed a significant decrease in the CVA index during 2050.

However, the suggested adaptive strategies showed a decrease in the CVA index during 2100. The CVA indices of the A_2O process were affected in the O.1 and O.3 strategies in 2100, but were not affected in the O.2 strategy. However, the A_2O process was influenced by the O.2 strategy in 2100 by a decrease in the EQI. The O.2 strategy, which increased the recycling fraction for increasing the SRT was not enough to affect the CVA index of the A_2O process. The CVA indices of the VIP process during 2100 were considerably decreased after application of O.1-O.3 adaptive strategies. The O.1 strategy for the VIP process during 2100 showed a decrease in ACF and ACW simultaneously. This was a result of the low T-P concentration of the oxic reactor effluent due to chemical precipitation. After the chemical precipitation process with alum, the T-P concentration of effluents was decreased and this could be connected to the decrease in the T-P concentration in the anoxic and oxic reactors, which could be connected to improvement in the luxury uptake and growth of PAOs [38,39]. Therefore, this adaptive strategy affected the ACF index as well as the ACW index.

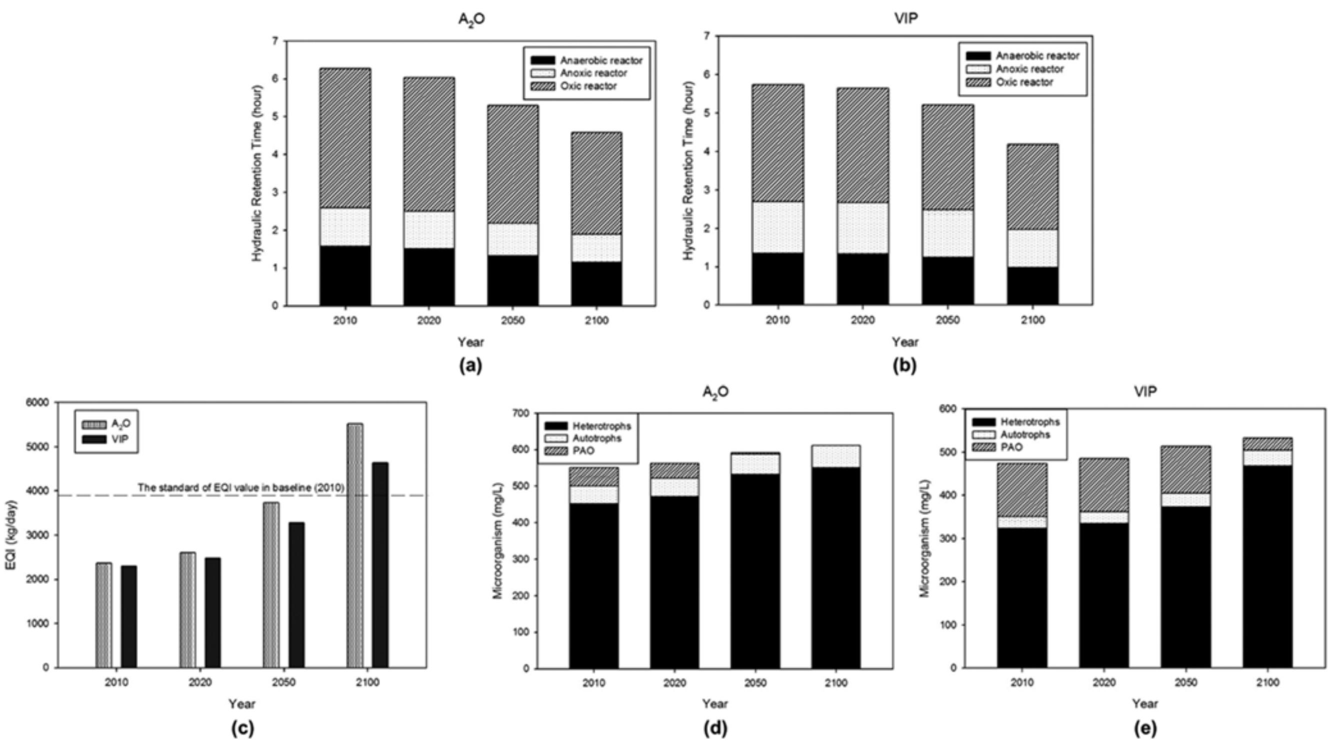

Fig. 6. Variation of performance and microorganisms' conditions in A_2O and VIP processes under A2 scenario: (a) HRT variation of A_2O process, (b) HRT variation of VIP process, (c) EQI variation of A_2O and VIP processes under A2 scenario, (d) Microorganisms' variation of A_2O process, and (e) Microorganisms' variation of VIP process.

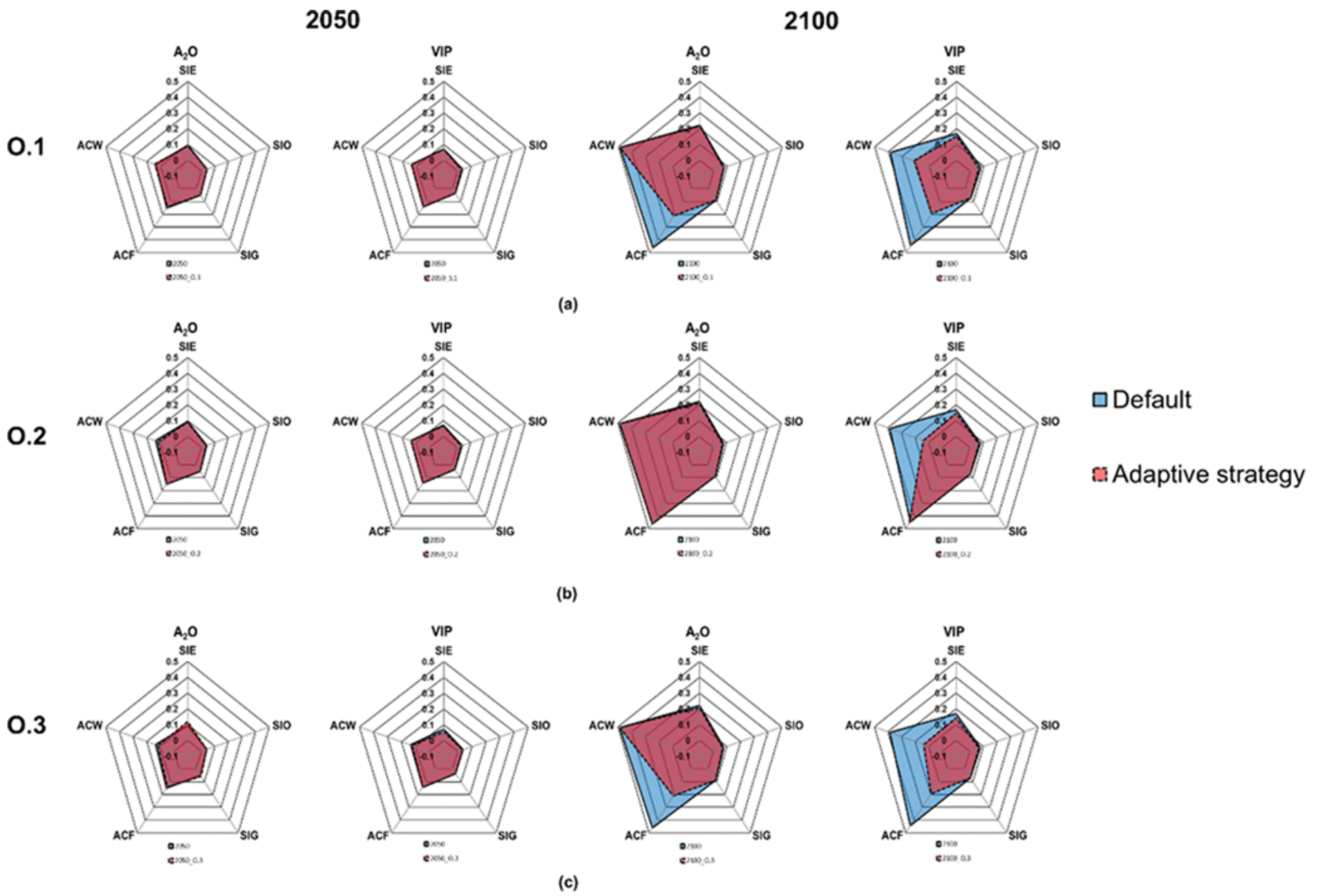

Fig. 7. Comparison of before and after application of operational adaptive strategies in A_2O and VIP during 2050 and 2100: (a) O.1 strategy, (b) O.2 strategy, and (c) O.3 strategy.

The O.2 strategy of the VIP process during 2100 showed a large decrease in the ACW, which indicated that the increase in the SRT during the winter period could be affected by the increment of the microorganism's concentration (autotrophs and PAO). This was a result of the increasing contact chance between pollutants and microorganisms due to increasing the recycling fraction. The O.3 strategy of the VIP process during 2100 showed a significant reduction in the ACF and ACW in the CVA index. This was a result of the combination of O.1 and O.2. The ACW of the O.3 strategy decreased more than that of the O.1 strategy, because of synergy between O.1 and O.2.

Fig. 8 presents the adaptive strategies modified via changing the design in the A_2O and VIP processes in 2050 and 2100. Figs. S4 to S6 also illustrate detailed information about operation adaptive strategies that included T-P and T-N effluent concentrations, EQI variation, and microorganism concentrations. After the application of design adaptive strategies in the A_2O process for 2050, all of the adaptive strategies showed a decrease in SIE and ACW indices. These strategies were affected by the decrease in effluent T-P concentration, which was a result of the increasing PAO concentrations in each reactor [38]. However, the T-N concentrations for each strategy in the A_2O process during 2050 were different from each other. Only the D.1 strategy increased the T-N concentration in the A_2O process, because the long retention time in the anaerobic reactor affected the consumption of carbon source and caused a decrease in the nitrogen removal efficiency. On the other hand, ACW indices in all of the strategies were increased after the application of these strategies in the VIP process during 2050. This was a result of a decrease in the nitrogen removal efficiency due to lack of a carbon source [40-42]. In particular, the increase in the ACW index in the D.2 strategy came from a decrease in the nitrification process. This was a result of the decrease in heterotroph concentration and the growth of PAOs. After application of adaptive strategies in the A_2O process during 2100, only the D.3 strategy showed the best improvement in SIE, ACW, and ACF.

The D.1 strategy increased the SIE index, although it produced a decrease in the ACF. The increase in the total volume of the WWTP produced a good AC after a flood. However, the increasing volume of the anaerobic reactor led to a decrease in the carbon source, which was needed in the nitrification process [40]. Therefore, the total EQI of the WWTP increased. The D.2 strategy showed the lowest improvement in the A_2O process during 2100. Although the T-P and T-N effluent concentrations were decreased after D.2 strategy application the EQI index was increased more by the growth of other pollutants (TSS, COD, etc.) [36]. The results of the adaptive strategy application in the VIP process during 2100 showed that the D.1 strategy was the best for the VIP process during 2100. Other strategies that included increments in the

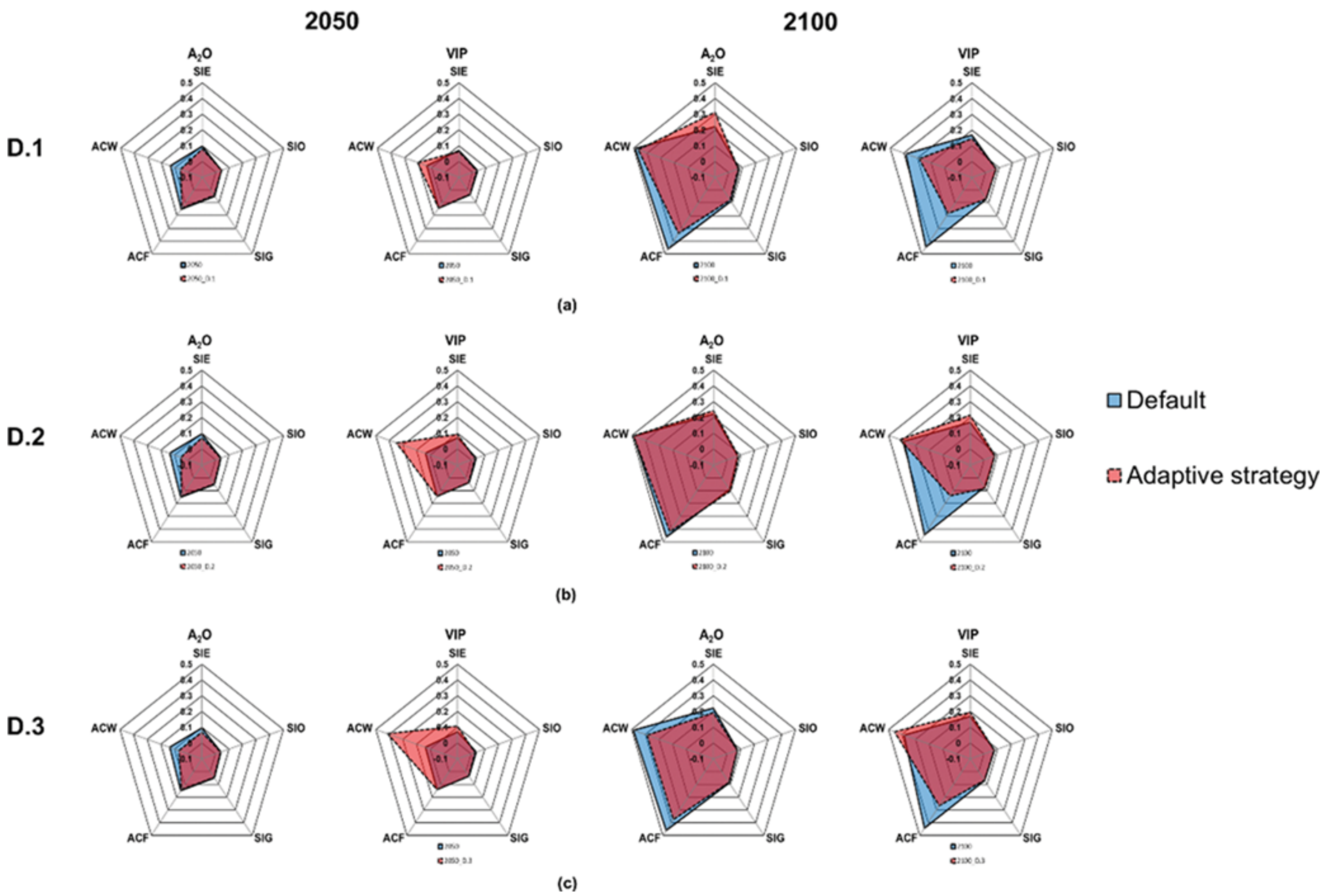

Fig. 8. Comparison of before and after application of design adaptive strategies in A_2O and VIP during 2050 and 2100: (a) D.1 strategy, (b) D.2 strategy, and (c) D.3 strategy.

Table 8. The comparisons of CVA indices of A_2O and VIP processes based on selected adaptive strategies

Process	Strategy	Year	SIE	SIO	SIG	ACF	ACW	CVA
A_2O	Default	2050	0.5768	0.2422	0.3021	0.3029	0.2690	0.3296
		2100	1.3297	0.4651	0.5284	0.9257	0.9760	0.8622
	D.2	2050	0.4300	0.2335	0.2957	0.2857	0.1044	0.2572
	D.3	2100	1.1607	0.4401	0.5182	0.7543	0.7727	0.7346
VIP	Default	2050	0.4269	0.2277	0.2157	0.2857	0.2709	0.2841
		2100	1.0178	0.4700	0.4310	0.8900	0.7717	0.7349
	O.3	2050	0.3245	0.2057	0.2146	0.2857	0.1124	0.2235
		2100	0.8598	0.4061	0.4244	0.3900	0.2775	0.4483

anoxic reactor volume produced the reverse effect via a decrease in heterotrophs and autotrophs. These situations were linked with EQI increase due to the lack of pollutant removal efficiency. The D.1 strategy in the VIP process during 2100 produced a decrease in heterotrophs. However, the amount was low, which indicated that the pollutant removal efficiency was preserved. Therefore, only the D.1 strategy generated a decrease in the CVA index in the VIP process during 2100.

4. Suggestion of Suitable Adaptive Strategies for WWTP Processes and Economic Assessments

The suggested adaptive strategies for climate change were assessed by variations in the CVA index and the radar graph in section 3.3. Based on these results, suitable adaptive strategies for A_2O and VIP processes were selected, and economic assessments based on Table 5 were conducted. Table 8 presents the CVA indices based on the application of adaptive strategies. The different strategies were selected for the different WWTP processes.

In the A_2O process, the D.2 and D.3 strategies were selected as the suitable adaptive strategies for 2050 and 2100, respectively. In section 3.3, all of the suggested adaptive strategies based on changing the design in the A_2O process during 2050, showed a similar effect in radar graphs. Therefore, the D.2 strategy was selected as

Table 9. Total operational cost of A_2O and VIP processes before and after application of adaptive strategies

Process	Adaptive strategy	Years	EQI (€)	SP (€)	PE (€)	AE (€)	Total cost (€)
A_2O	Default	2050	186,597	56,452	24,315	32,626	299,990
		2100	275,699	56,040	28,107	49,598	409,443
VIP		2050	164,184	66,224	52,937	26,156	309,501
		2100	232,164	72,320	61,184	40,487	406,156
A_2O	D.2	2050	188,565	55,638	24,314	115,66	280,083
	D.3	2100	217,065	74,349	61,184	39,973	392,570
VIP	O.3	2050	169,585	64,900	52,092	29,429	316,006
		2100	213,987	70,896	53,836	41,701	380,421

the most suitable adaptive strategy during 2050 by numerical comparison with CVA. The D.3 strategy was identified as the most suitable adaptive strategy during 2100, because the D.3 strategy only decreased the CVA index of the A_2O process during 2100 and this strategy had the linking point with the D.2 strategy during 2050.

In the VIP process, the suitable adaptive strategy was the O.3 strategy for 2050 and 2100. Similarly, there were no significant differences between the suggested strategies based on radar graphs with the A_2O process during 2050. The O.3 strategy was selected as a suitable strategy for the VIP process during 2050 based on the numeric comparison of CVA. In addition, the O.3 strategy for the VIP process showed the lowest CVA index between the other suggested strategies during 2100. Consequently, the adaptive strategies selected as suitable were the D.2 and D.3 strategies for the A_2O process and the O.3 strategy for the VIP process.

Table 9 illustrates the comparison of target processes' total operational costs before and after application of adaptive strategies. Almost all of the strategies produced a decrease in the total operational cost by the decrease in sludge production or the EQI index. However, the operational cost of the VIP process during 2050 was increased after application of the O.3 strategy due to the increment of EQI and the requirement of air pumping energy. However, the selected adaptive strategies for WWTP processes provided more high pollutant removal efficiency as well as economic benefits.

The availability of tools for the evaluation of impacts caused by climate change in WWTP at process level is important to design more optimal and cost-effective procedures for the future. This approach can be linked with complementary studies to perform multi-objective optimization using different scenarios with the aim of prepare educated planning decisions [27,33,36,37].

This study included general factors for overall regions seeking to evaluate vulnerability of WWTP at process level considering climate change events such as flood and drought. Therefore, the proposed method is applicable for all regions since it is more focused on the process itself and not into a region. When flood is the main issue, vulnerability of drought decreases, and when drought is occurring, flood vulnerability is reduced automatically. As a result, the method can be applied for all regions without changing the formula.

CONCLUSIONS

We have suggested a climate change vulnerability assessment index at the process-level. The climate change vulnerability assessment index (CVA index) was developed based on effluent conditions, operational costs, greenhouse gas emissions, and AC after floods and during the winter season. Major WWTP processes (A_2O, BarDenPho, MUCT, and VIP) were chosen as target processes to assess climate change vulnerability in four specific years (2010, 2020, 2050, and 2100). The A2 carbon emission scenario for 2100 was used as the background scenario for this research. After the vulnerability assessment at the process-level, A_2O and VIP processes were identified as the processes most vulnerable to climate change due to their smaller total reactor sizes. Simple adaptive strategies were suggested by analyzing each vulnerability indicator using radar graphs. The A_2O and VIP processes with adaptive strategies showed much smaller vulnerability to climate change than before. Therefore, the results of this study can be useful for assessing vulnerability to climate scenarios and to evaluate adaptive strategies in WWTP at plant level for all regions.

ACKNOWLEDGEMENTS

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SUPPORTING INFORMATION

Additional information as noted in the text. This information is available via the Internet at http://www.springer.com/chemistry/journal/11814.

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Supporting Information

Vulnerability assessment index at process-level for the identification of adaptive strategies in wastewater treatment plants under climate change

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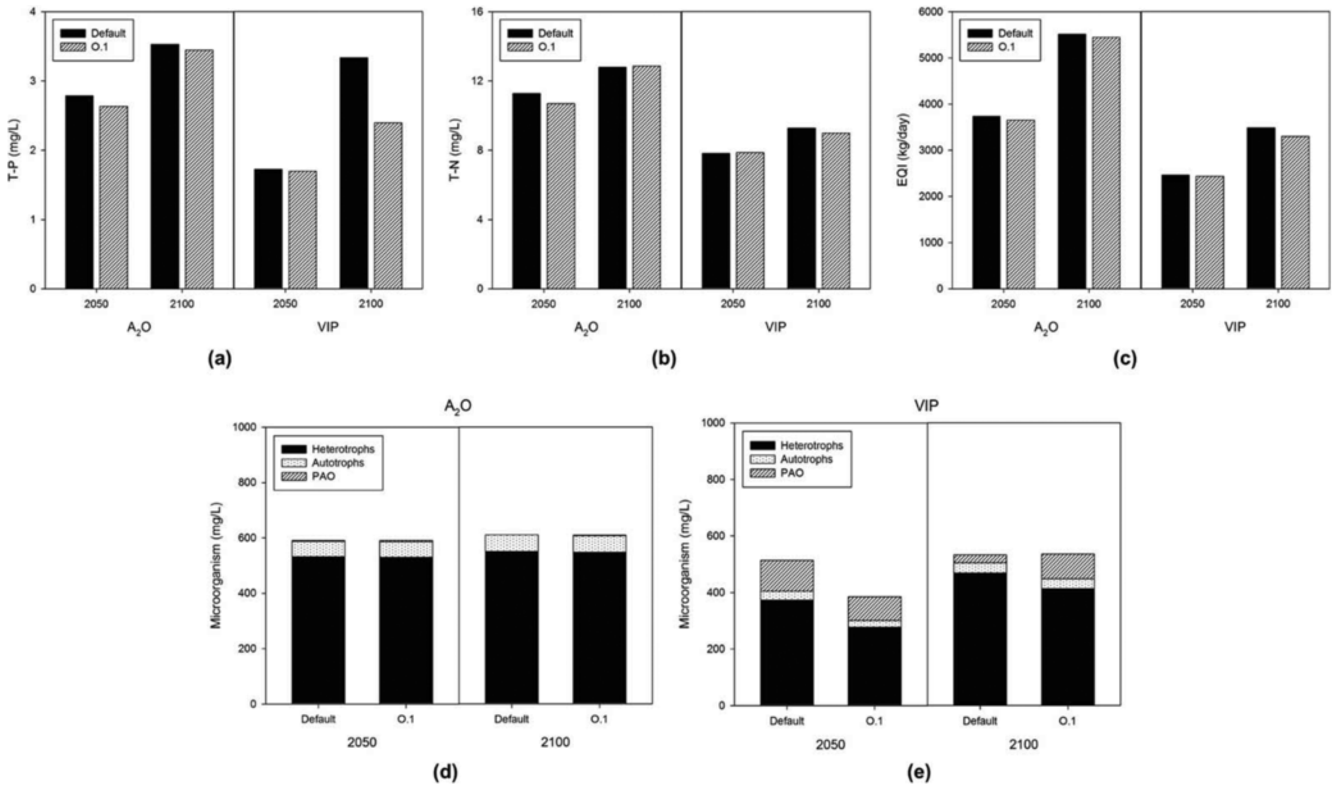

Fig. S1. Comparison of process performance and microorganism conditions before and after application of O.1: (a) T-P concentration, (b) T-N concentration (c) EQI index, (d) Microorganisms in A_2O, (e) Microorganisms in VIP.

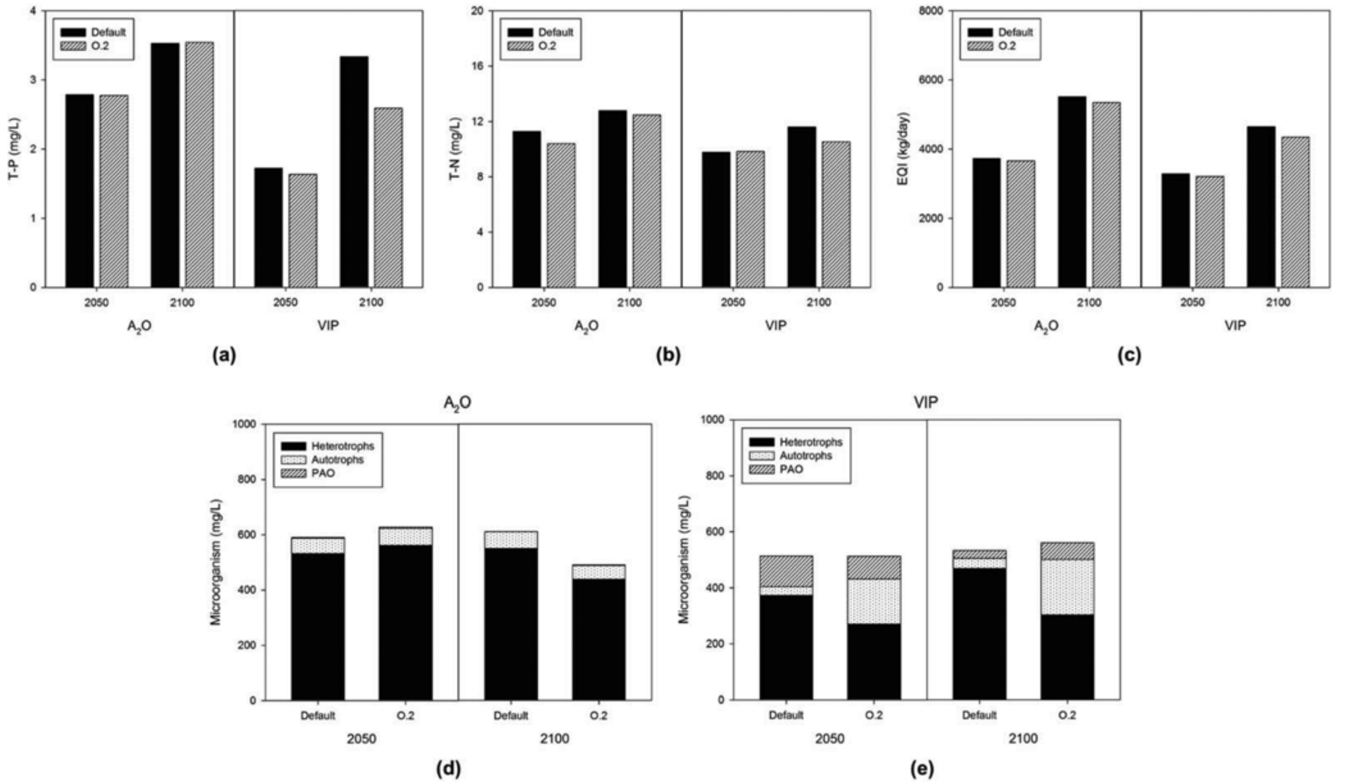

Fig. S2. Comparison of process performance and microorganism conditions before and after application of O.2: (a) T-P concentration, (b) T-N concentration (c) EQI index, (d) Microorganisms in A_2O, (e) Microorganisms in VIP.

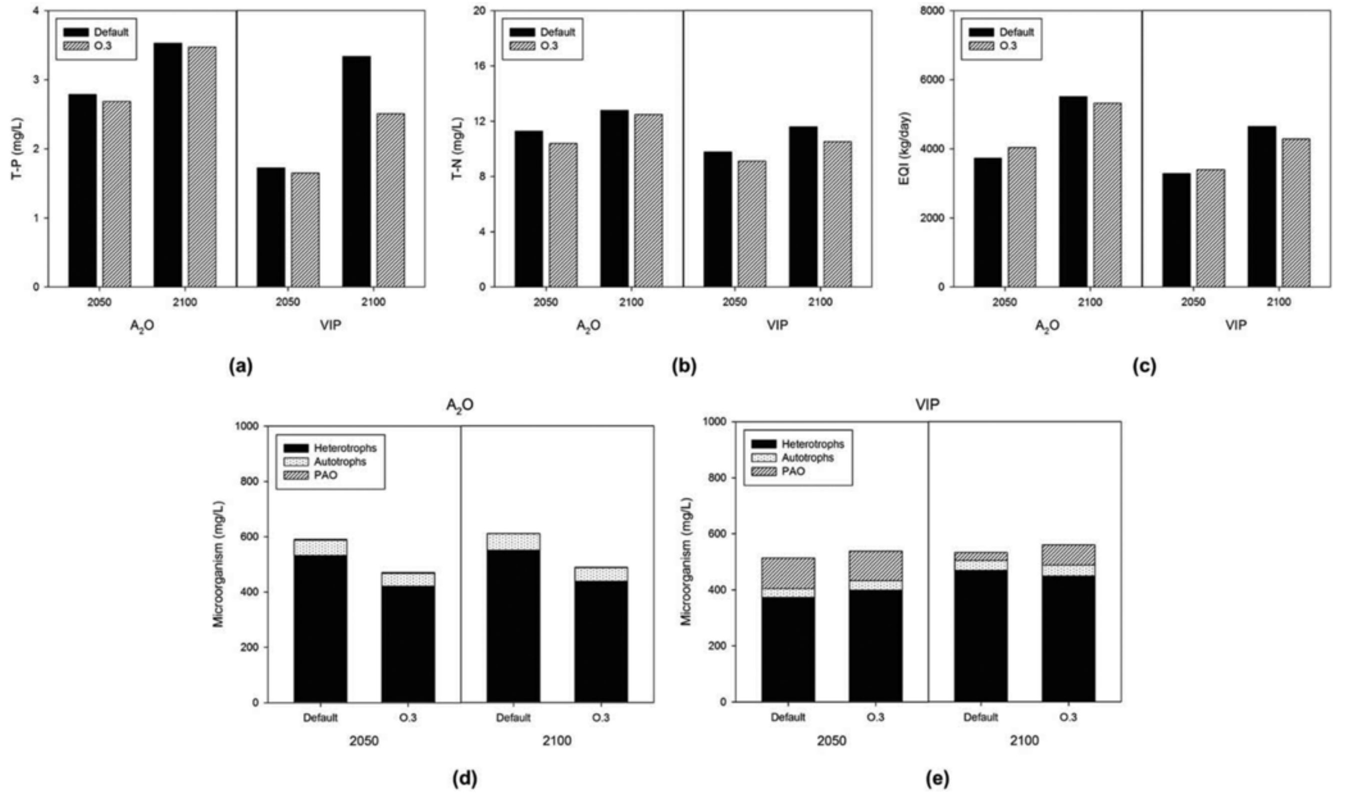

Fig. S3. Comparison of process performance and microorganism conditions before and after application of O.3: (a) T-P concentration, (b) T-N concentration (c) EQI index, (d) Microorganisms in A_2O, (e) Microorganisms in VIP.

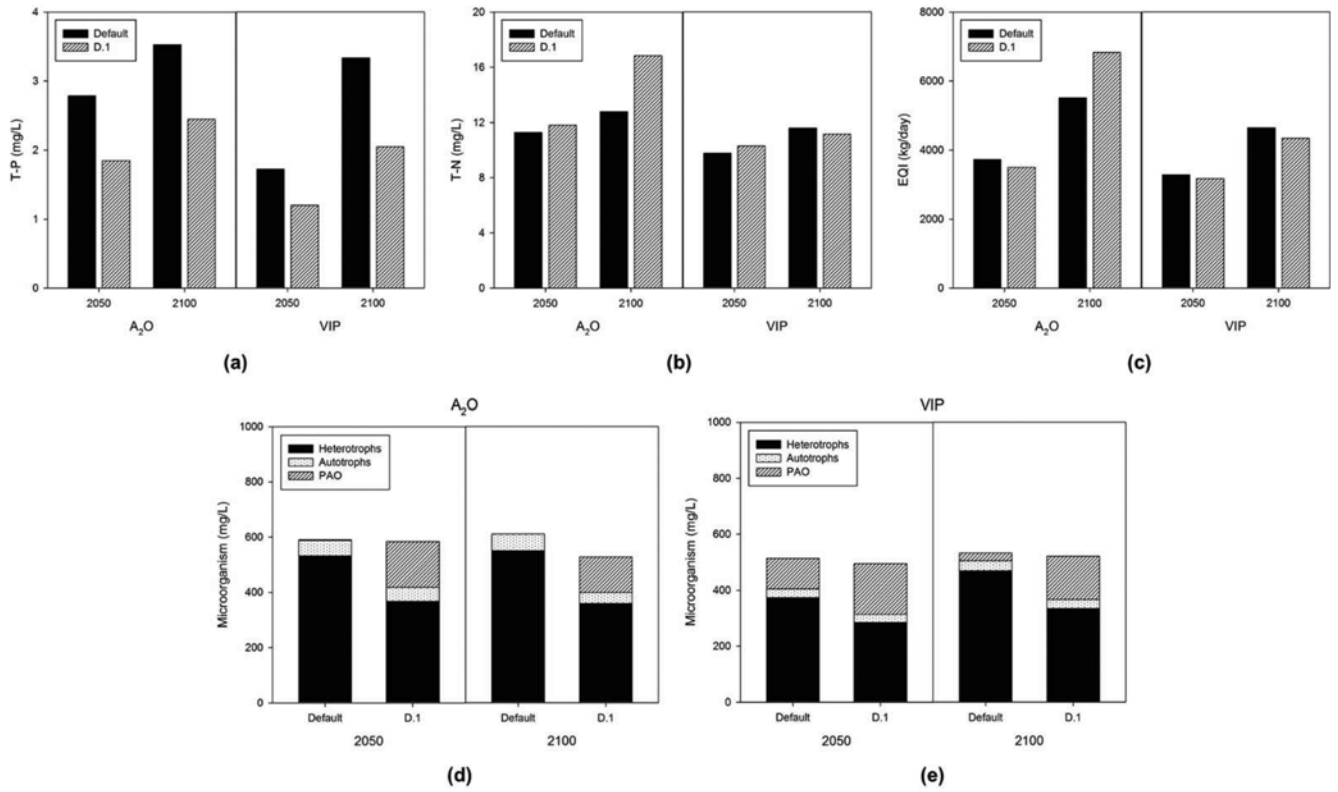

Fig. S4. Comparison of process performance and microorganism conditions before and after application of D.1: (a) T-P concentration, (b) T-N concentration (c) EQI index, (d) Microorganisms in A_2O, (e) Microorganisms in VIP.

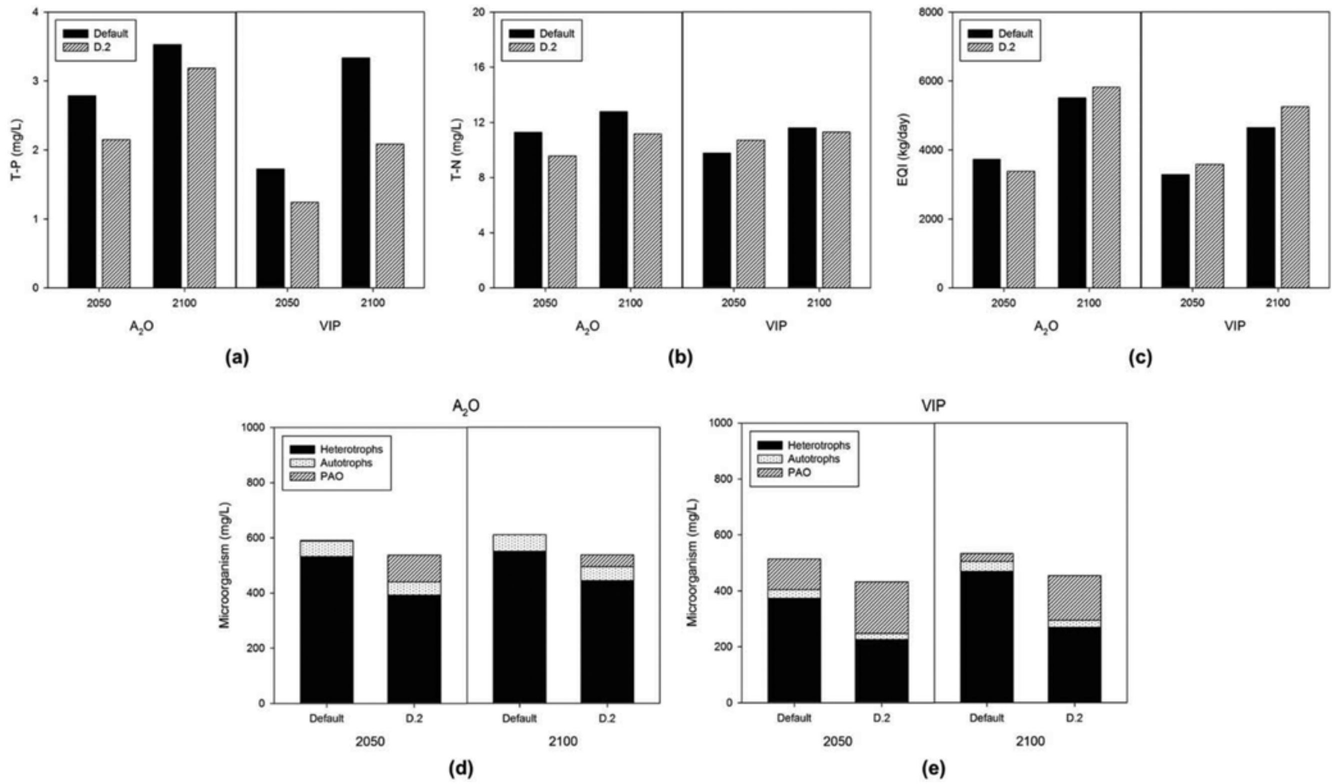

Fig. S5. Comparison of process performance and microorganism conditions before and after application of D.2: (a) T-P concentration, (b) T-N concentration (c) EQI index, (d) Microorganisms in A_2O, (e) Microorganisms in VIP.

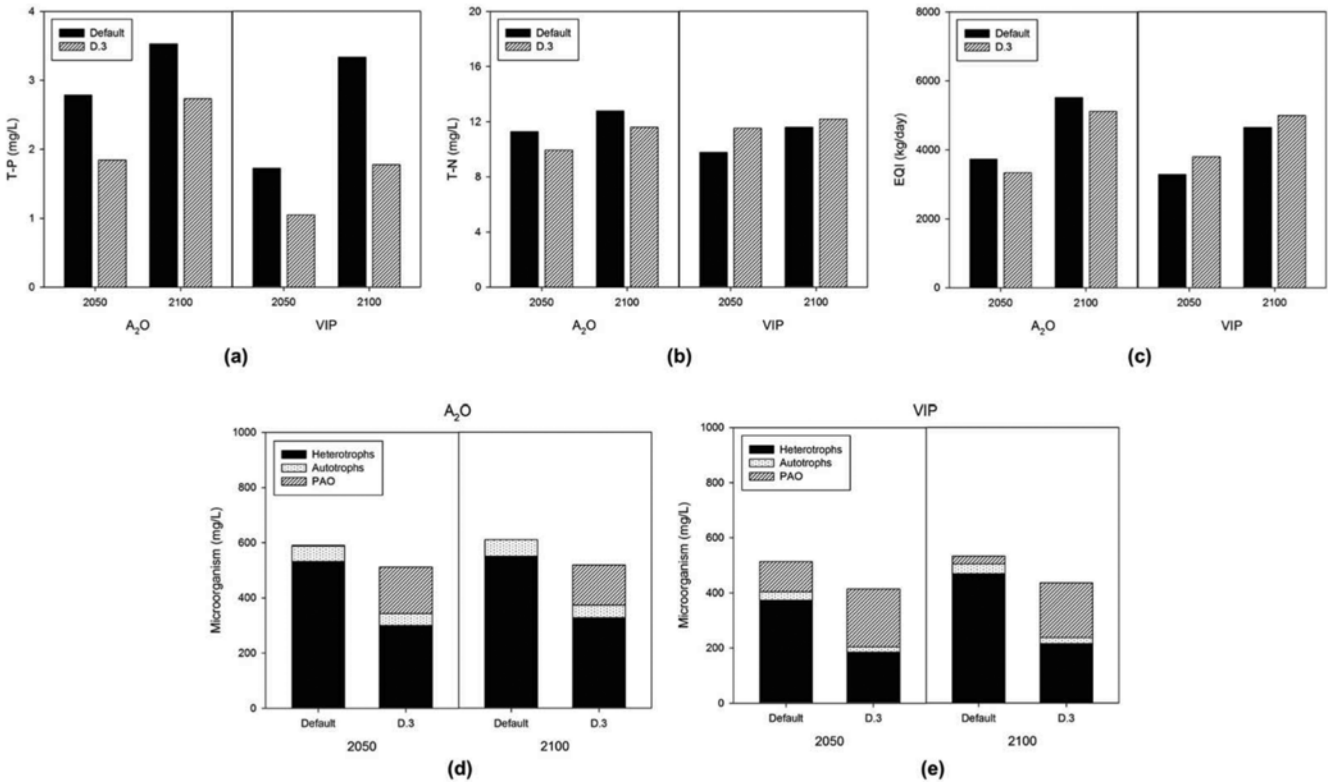

Fig. S6. Comparison of process performance and microorganism conditions before and after application of D.3: (a) T-P concentration, (b) T-N concentration (c) EQI index, (d) Microorganisms in A_2O, (e) Microorganisms in VIP.