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Pareto-optimal solutions for environmental flow schemes incorporating the intra-annual and interannual variability of the natural flow regime

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[1] The temporal variations of natural flows are essential elements for preserving the ecological health of a river which are addressed in this paper by the environmental flow schemes that incorporate the intra-annual and interannual variability of the natural flow regime. We present an optimization framework to find the Pareto-optimal solutions for various flow schemes. The proposed framework integrates (1) the range of variability approach for evaluating the hydrologic alterations; (2) the standardized precipitation index approach for establishing the variation criteria for the wet, normal, and dry years; (3) a weir operation model for simulating the system of flows; and (4) a multiobjective optimization genetic algorithm for search of the Pareto-optimal solutions. The proposed framework is applied to the Kaoping diversion weir in Taiwan. The results reveal that the time-varying schemes incorporating the intra-annual variability in the environmental flow prescriptions promote the ecosystem and human needs fitness. Incorporation of the interannual flow variability using different criteria established for three types of water year further promotes both fitnesses. The merit of incorporating the interannual variability may be superimposed on that of incorporating only the intra-annual flow variability. The Pareto-optimal solutions searched with a limited range of flows replicate satisfactorily those obtained with a full search range. The limited-range Pareto front may be used as a surrogate of the full-range one if feasible prescriptions are to be found among the regular flows.

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1. Introduction

[2] Developments of water resources for various purposes, such as irrigation, hydropower, industry, and domestic uses, are well known for their impacts on riverine ecosystems. These impacts are mainly caused by the alteration of hydrologic regimes associated with reservoir and/or weir operations. Rivers downstream of such facilities typically experience a loss of natural variability in flow magnitude, frequency, duration, timing, and rate of change. Flow regulation also alters geomorphic processes, physical habitat, nutrient cycling, water quality, temperature, and biotic interactions, thus deteriorates the health of the riverine ecosystem. In an effort to mitigate these impacts and support sustainable ecosystems, managed releases of water to meet the instream flow requirements, or more popularly termed "environmental flows" in recent years, have increasingly received attention from the communities of water resources management and river restoration [*Wohl et al.*, 2005; *Richter et al.*, 2006].

[3] A key challenge for environmental flow assessment is to determine how much of the original flow regime should continue to flow down a river and onto its floodplains in order to maintain the valued features of an ecosystem. A vast body of formal methodologies now exists for evaluating environmental flow requirements. An exhaustive and comprehensive global review provided by *Tharme* [2003] documented some 207 individual methodologies recorded for 44 countries. Over the three decades of environmental flow research, four trends have marked its evolution [*National Research Council*, 2005]: (1) from single minimal flows to flow regimes, (2) from a single-species focus to a holistic ecosystems approach, (3) from the study of instream (or stream channel) needs to that including out-of-stream (riparian and floodplain) areas, (4) from a hydrology dominated field to an interdisciplinary one. The Instream Flow Council offers an updated definition of instream flows [*Instream Flow Council*, 2004, p. 9]:

> The objective of an instream flow prescription should be to mimic the natural flow regime as closely as possible. Flow regimes must also address instream and out-of-stream needs and integrate biotic and abiotic processes. For these reasons, inter- and intra-annual instream flow prescriptions are needed to preserve the ecological health of a river.

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[4] A considerable amount of river ecology researches have recognized the importance of natural flow variability in sustaining the biodiversity and ecosystem integrity. As a result, the "natural flow regime" has been emerging as a paradigm for river management [*Poff et al.*, 1997]. To characterize the flow regime, a number of hydrologic index systems have been proposed. For example, *Richter et al.* [1996] proposed 32 indices that may serve as the indicators of hydrologic alteration (IHA). *Olden and Poff* [2003] reviewed 171 hydrologic indices and offered the guidelines for selection of indicators. *Suen et al.* [2004] presented a suite of ecohydrologic indicators used for the rivers in Taiwan. Despite many examples can be found where researchers have employed various indices to assess the hydrologic changes induced by flow regulations (see the IHA Applications Database prepared by The Nature Conservancy at http://www.nature.org/initiatives/freshwater/files/iha_apps.pdf), studies that incorporated the natural flow regime to optimize water release strategies were rarely reported, primarily because of a lack of widely accepted tools suitable for quantifying the ecological fitness of environmental flow prescriptions. Though previous attempts have been made to quantify the ecological fitness using the physical habitat and population sizes [*Sale et al.*, 1982; *Cardwell et al.*, 1996; *Jager and Rose*, 2003], they were mainly concerned with the fishery but not maintenance of the biodiversity and ecosystem integrity associated with the natural flow variations.

[5] Only recently does incorporation of the regime-based environmental flows in water resources planning and management become practicable, thanks to the introduction of quantitative methods such as the range of variability approach (RVA) and intermediate disturbance hypothesis (IDH) approach. The RVA uses natural flow records to establish the IHA target ranges. The management goal is to attain the target ranges as frequently as the natural flow regime, which is expected to promote the riverine ecosystem [*Richter et al.*, 1997]. A series of studies based on the RVA have been conducted recently. For example, *Shiau and Wu* [2004a] employed an RVA-based modeling approach to investigate the effect of a proposed water release plan on restoring the natural flow regime downstream of the Chi-Chi diversion weir, Taiwan. *Shiau and Wu* [2004b] applied the RVA in evaluating the tradeoffs between the ecosystem and human needs objectives associated with various combinations of water withdrawal and instream flow release for a proposed Taitung weir in Taiwan. *Shiau and Wu* [2006] further combined the RVA with a compromise programming to search the optimal solution of an objective function aggregating multiple water allocation criteria of the Kaoping diversion weir (Taiwan). *Shiau and Wu* [2007] went on to present a dynamic corridor-searching algorithm to seek the optimal time-varying flow prescriptions that incorporate the intra-annual (or within-year) variability of the natural flow regime. The Pareto-optimal solutions of the multiobjective optimization problem, however, were not addressed in this series of studies.

[6] On the other hand, the IDH approach assumes that ecosystems are healthier under disturbances that are neither too small nor too large in magnitude and frequency. For each hydrologic indicator, instead of setting the upper and lower targets, the ecological fitness is quantified using a Gaussian fuzzy membership function. The management goal is to attain the intermediate level pursuing the highest possible membership values. On the basis of the IDH approach, for example, *Suen and Eheart* [2006] employed a multiobjective optimization genetic algorithm (GA) to find the Pareto sets of operational rules for the Shihmen reservoir (Taiwan). Their proposed operational rules were, however, scheduled for 36 10-day periods aiming to reflect only the intra-annual variability of the natural flows.

[7] None of the previous studies has taken into account the interannual (or between-year) variability, which is in contrast to the current trend of environmental flow practices that emphasize maintenance of both the interannual and intra-annual variability of the natural flow regime [*Richter et al.*, 2006]. Thus, in this study we incorporate the intra-annual and interannual variability of the natural flow regime in an RVA-based optimization framework to seek the environmental flow schemes that are aimed to balance the ecosystem and human needs objectives of a weir operation. The intra-annual variability is maintained by the hydrograph components of environmental flows prescribed with the time-varying (i.e., semiannually, quarterly, and monthly varying) schemes. The interannual flow variability is addressed by different IHA target ranges established for three types of water year (i.e., wet, normal, and dry years). A multiobjective optimization GA is employed to find the Pareto-optimal solutions for various flow schemes. The results demonstrate the merit of taking into account different temporal scales of the natural flow variations. This study differs from the previous ones because, to our knowledge, the Pareto sets of environmental flow prescriptions that incorporate the interannual variability have not been published in a peer-reviewed journal.

2. Study Case

2.1. Overview

[8] The Kaoping diversion weir (in southern Taiwan) is selected to address the problem of multiobjective optimization because of its dual task to meet the human and ecosystem needs (i.e., water supply and maintenance of natural flow characteristics). The Kaoping diversion weir is located in the midstream of the Kaoping Creek (Figure 1). The Kaoping Creek basin, with a total channel length of 171 km and drainage area of 3,257 km^2, is the largest one in Taiwan. The alluvial plain of the Kaoping Creek is a major agricultural area, where the overdraft of groundwater had led to severe subsidence and seawater intrusion. To mitigate these impacts and provide an alternative source of water supply, the Kaoping diversion weir was constructed from 1992 and completed in 1999.

[9] Monthly flow characteristics (1951–2001) of the Lilin Bridge gauge station, located at immediately upstream of the diversion weir, are shown in Table 1. These data demonstrate a highly fluctuating and unevenly distributed flow pattern typical of the rivers in Taiwan. The water supply objectives of the Kaoping diversion weir are to meet the agricultural and domestic demands. For simplicity, these water demands are combined in a single human needs objective. The projected monthly diversions are also shown in Table 1 [*Water Conservancy Agency* (*WCA*), 2000], which total 1,064 million m^3 per year.

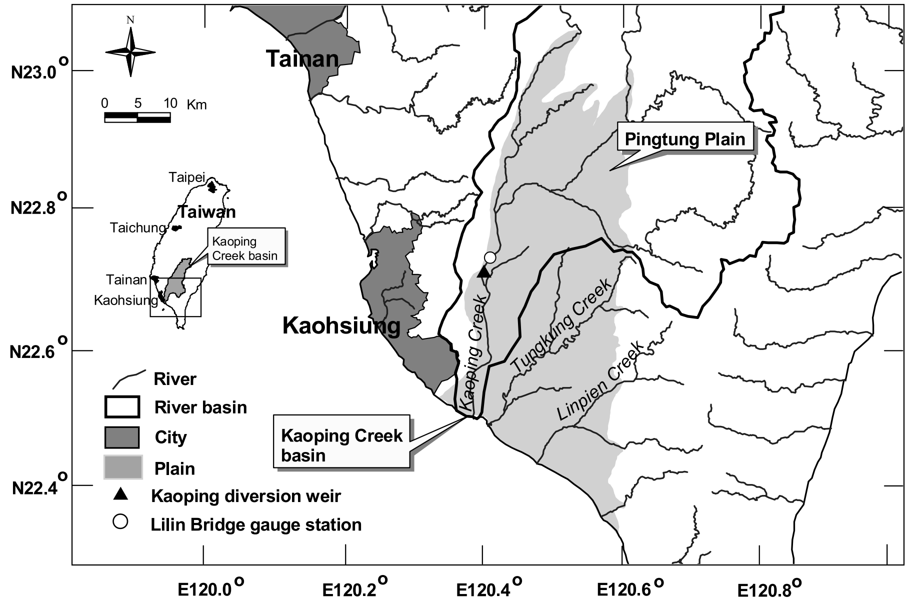

Figure 1. Kaoping Creek basin and Kaoping diversion weir.

[10] Currently a constant minimal flow of 9.5 m^3/s is released from the Kaoping diversion weir for the purpose of environmental protection [*WCA*, 2000], which is unlikely to create sufficient resemblance to the natural flow regime [*Shiau and Wu*, 2006]. We assume that the operational goal of the Kaoping diversion weir is to supply the water demands while retaining the "targeted flow variability." Since the postdiversion flows vary as a function of the environmental flow prescriptions, a weir operation model is used to simulate the flows diverted to supply the human demands and those released for the ecosystem preservation.

2.2. Weir Operation Model

[11] The system of flows in the weir operation model is depicted in Figure 2, where two flow criteria are to be met at time t, including the projected flow diversions Q_{PD}^t and environmental flow prescriptions Q_{EF}^t; Q_I^t denotes the natural (or prediversion) inflow; Q_{AD}^t denotes the amount of flow actually diverted for water supplies; Q_O^t denotes the postdiversion outflow. The monthly projected diversions Q_{PD}^t are summarized in Table 1; Q_{EF}^t is the only decision variable whose values need to be specified in the simulation. The operational rules of the Kaoping diversion weir are given as follows:

$$\begin{cases} Q_O^t = Q_I^t, Q_{AD}^t = 0 & \text{if} \quad Q_I^t \le Q_{EF}^t \\ Q_O^t = Q_{EF}^t, Q_{AD}^t = Q_I^t - Q_{EF}^t & \text{if} \quad Q_{EF}^t < Q_I^t \le Q_{EF}^t + Q_{PD}^t \\ Q_O^t = Q_I^t - Q_{PD}^t, Q_{AD}^t = Q_{PD}^t & \text{if} \quad Q_I^t > Q_{EF}^t + Q_{PD}^t \end{cases} \tag{1}$$

where the human demands are to be supplied only when the ecosystem need criterion is met, indicating that a higher priority is given to the environmental flows. These operational rules of the Kaoping diversion weir are currently implemented by the Water Resources Agency (Taiwan) with a constant value of Q_{EF}^t = 9.5 m^3/s. Here we modify the operational rules by allowing the values of Q_{EF}^t to vary with time. The daily flow records (1951–2001) of the Lilin Bridge gauge station are used in our simulations as the inflow series Q_I^t. In practice, the environmental flow releases and flow diversions are controlled with the gates following the allocation rules, and the excess flows are discharged to downstream through a spillway. The outflow series Q_O^t are used to assess the hydrologic alterations (see section 3.1). The flow series Q_{AD}^t actually diverted for human demands are used to evaluate the deficit of water supplies, as described below.

2.3. Water Deficit Index

[12] The shortage ratio, *SR*, is used in this study as an index of water supply deficit [*Cancelliere et al.*, 1998], which is defined by

$$SR = \frac{\sum_{t=1}^{N} \left| \min\{Q_{AD}^t - Q_{PD}^t, 0\} \right|}{\sum_{t=1}^{N} Q_{PD}^t} \times 100\% \tag{2}$$

where N = total number of days in the simulation period. The value of *SR* represents the human needs objective to be

Table 1. Monthly Flow Characteristics (1951–2001) and Projected Monthly Diversions at the Kaoping Diversion Weir[a]

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Max Flow	69.8	131.6	278.8	357.3	786.3	1812.8	1385.4	1958.0	1381.4	544.0	350.2	171.1
Mean Flow	26.4	27.3	37.3	57.7	184.9	546.2	466.1	715.4	481.1	182.5	81.9	44.5
Min Flow	2.7	1.2	2.3	8.2	13.8	25.1	25.1	31.0	87.7	23.5	18.6	17.5
Projected Monthly Diversion	22.6	22.5	22.1	22.1	28.1	45.3	45.4	47.5	47.0	47.4	28.4	25.3

[a]Units in m^3/s.

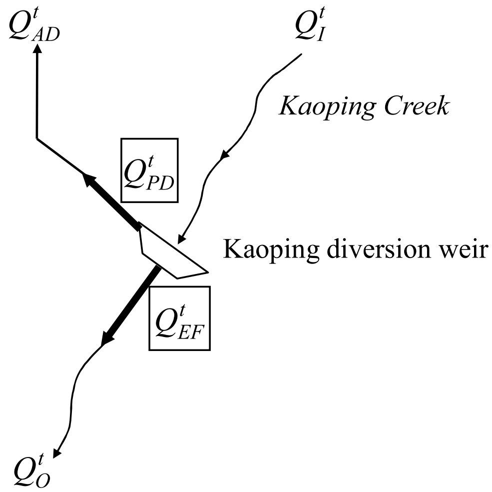

Figure 2. System of flows for the Kaoping diversion weir operation. Flows in the boxes represent the projected diversions (Q^t_{PD}) and environmental flow prescriptions (Q^t_{EF}); Q^t_I and Q^t_O denote the inflows and outflows, respectively; Q^t_{AD} denotes the amount of flow actually diverted for water supplies; the superscripts t denote time.

minimized with the multiobjective optimization algorithm (see section 3.4).

3. Methods

3.1. RVA

[13] The RVA employs a set of IHA to characterize the prediversion (or natural) and postdiversion (or altered) flow regimes [*Richter et al.*, 1997]. The 32 IHA, shown in Table 2, are grouped by five categories, i.e., magnitude, duration, timing, frequency, and rate of change. Each IHA is ecologically relevant. For instance, the annual extreme flows provide a measure of the fluvial conditions that structure the channel form and physical habitat. The exchange of nutrient between the channel and floodplains is intimately linked to the frequency and duration of the high/low pulses. For more details on the IHA, the readers are referred to the original work [*Richter et al.*, 1997; *Poff et al.*, 1997].

[14] The IHA are evaluated annually. For each of the 32 IHA, a target range is determined with the natural (or preimpacted) flow data. In this study, the IHA target range is bracketed by the 25th- and 75th-percentile values, implying that 50% of the preimpacted years would have the IHA values falling in this target range [*Richter et al.*, 1998]. If the postimpacted frequency of attaining the IHA target range deviates much from 50%, such an indicator is regarded as highly altered. To quantify the deviation of the postimpacted flow regime from the natural one, the degree of hydrologic alteration is evaluated by

$$D_i = \frac{N_{o,i} - N_e}{N_e} \times 100\% \tag{3}$$

where D_i = degree of hydrologic alteration for the ith indicator; $N_{o,i}$ = observed number of years with the postimpacted IHA values falling in the target range (for the ith indicator); N_e = expected number of years in which the IHA would fall in the target range = $p \cdot N_T$, where N_T = total number of observed years, and p = 50% for the target range bracketed by the 25th- and 75th-percentile values. *Richter*

Table 2. Indicators of Hydrologic Alteration (IHA) Used in the Range of Variability Approach (RVA)

IHA	Units
Group 1: Magnitude of Monthly Flows	
Mean flow of each calendar month	m^3/s
Group 2: Magnitude and Duration of Annual Extreme Flows and Base Flow Condition	
Annual 1-day minimum flow	m^3/s
Annual 1-day maximum flow	m^3/s
Annual 3-day minimum flow	m^3/s
Annual 3-day maximum flow	m^3/s
Annual 7-day minimum flow	m^3/s
Annual 7-day maximum flow	m^3/s
Annual 30-day minimum flow	m^3/s
Annual 30-day maximum flow	m^3/s
Annual 90-day minimum flow	m^3/s
Annual 90-day maximum flow	m^3/s
Base flow condition (annual 7-day minimum flow divided by annual mean flow)	–
Group 3: Timing of Annual Extreme Flows	
Julian date of annual 1-day minimum flow	
Julian date of annual 1-day maximum flow	
Group 4: Frequency and Duration of High and Low Pulses [a]	
Number of high pulses in each year	
Number of low pulses in each year	
Mean duration of high pulse	days
Mean duration of low pulse	days
Group 5: Rate and Frequency of Flow Changes	
Rise rate (mean of all positive differences between consecutive daily flows)	$m^3/s/d$
Fall rate (mean of all negative differences between consecutive daily flows)	$m^3/s/d$
Number of flow reversals	

[a]High and low pulses are those periods in which the daily flows are above the 75th- and below the 25th-percentile preimpact daily flows, respectively.

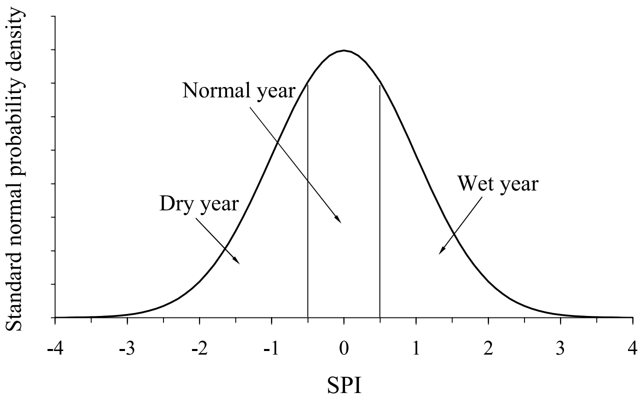

Figure 3. Classification of wet, normal, and dry years based on standardized precipitation index (SPI).

et al. [1998] proposed a simple three-class system for evaluation of the individual D_i, in which the value of $|D_i|$ ranging between 0–33%, 33–67%, and 67–100% is classified as the low, moderate, and high alterations, respectively. Since the individual values of D_i may belong to different alteration classes, an integrative index is used to define the overall degree of hydrologic alteration, i.e.,

$$D_o = \left(\frac{1}{32} \sum_{i=1}^{32} D_i^2 \right)^{1/2} \tag{4}$$

To minimize D_o equivalently means to best maintain the natural flow regime, which is thus used in this study as a surrogate objective of the ecosystem needs (see section 3.4).

3.2. Interannual Flow Variability

[15] To incorporate the interannual flow variability in this study, three types of water year are defined using the standardized precipitation index (SPI) approach [*McKee et al.*, 1993]. The SPI was originally proposed for detection of droughts using the long-term precipitation data. It has ever since gained popularities for the drought analyses because of its simplicity [*Heim*, 2002]. Some recent applications of the SPI in the analyses of drought frequency, duration, spatial pattern, severity, vulnerability, and the effect of record length can be found in work by *Hayes et al.* [1999], *Lana et al.* [2001], *Bonaccorso et al.* [2003], *Tsakiris and Vangelis* [2004], *Wu et al.* [2005], *Sönmez et al.* [2005], *Vicente-Serrano* [2006], and *Shiau* [2006].

[16] Here, the annual total runoff is used to define the wet, dry, and normal water years. The value of SPI is given by an inverse standard normal transformation, i.e.,

$$SPI = \Phi^{-1}[F_R(r)] \tag{5}$$

where r = annual runoff; F_R = cumulative distribution function (cdf) of the annual runoff; Φ^{-1} = inverse cumulative standard normal distribution. A positive SPI indicates that the annual runoff is greater than the median, whereas a negative SPI indicates that the annual runoff is less than the median. In this study, the values of SPI ranging between −0.5 and 0.5 are used to define the normal years (Figure 3), the values of SPI >0.5 define the wet years, whereas the values of SPI <−0.5 define the dry years, following the criteria suggested by the U.S. Drought Monitor Program [*Svoboda et al.*, 2002]. As a result, the probabilities corresponding to the wet and dry years are both 31%, while the probability corresponding to the normal years is 38%.

[17] The annual runoffs at the Lilin Bridge gauge station (1951–2001) can be best fitted with a gamma distribution (Figure 4); its shape and scale parameters (=7.44 and 1012.59) were determined by the method of maximum likelihood. Accordingly, the threshold annual runoffs used to define the wet and dry years are 8,625 and 5,933 million m^3 (Figure 4); the resulting numbers of the wet, normal, and dry years are 18, 19, and 14, respectively. The target ranges of the 32 IHA are then established for each type of water year. Table 3 shows the lower and upper targets (=25th- and 75th-percentile values) of the 32 IHA determined using the daily flow data from different types of water year and from all years (1951–2001). It should be noted that for each type of water year discussed here, the data length is less than 20 years, which raises an issue regarding the statistically valid data length. Although *Richter*

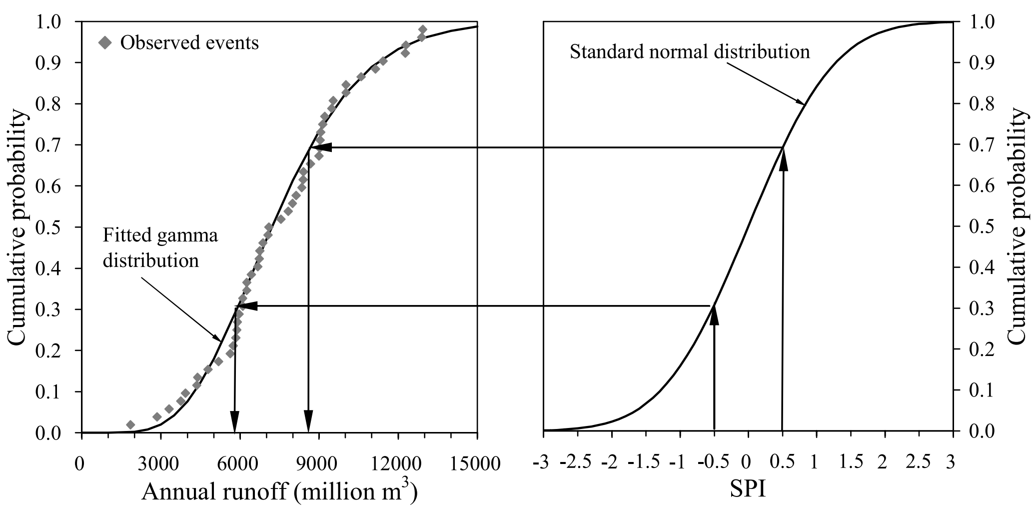

Figure 4. Determination of annual runoff thresholds for different types of water year. The SPI values of 0.5 and −0.5 are transformed from the standard normal to the fitted gamma distribution for defining the ranges of annual runoff corresponding to the wet, normal, and dry years.

Table 3. IHA Target Ranges Determined Using the Daily Flows From All Years (1951–2001) and From the Wet, Normal, and Dry Years[a]

		All Years		Wet Years		Normal Years		Dry Years	
Group	IHA	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
1	Jan	16.4	32.1	22.0	43.7	15.8	29.3	20.5	29.6
	Feb	14.7	31.8	14.7	41.8	14.7	29.2	12.6	25.9
	Mar	14.4	30.1	15.0	61.7	15.7	52.4	14.3	22.7
	Apr	16.8	57.9	19.4	123.4	21.9	74.9	14.4	34.5
	May	69.5	305.6	107.6	383.7	70.0	305.6	28.1	146.8
	Jun	218.0	783.0	432.1	1056.6	191.7	597.4	131.1	546.8
	Jul	243.3	645.7	433.7	729.1	246.2	700.6	105.4	411.5
	Aug	336.6	1093.1	587.0	1560.7	344.9	1065.7	221.4	403.7
	Sep	251.9	614.8	283.2	732.4	286.4	614.8	200.2	532.1
	Oct	100.7	222.5	110.9	290.0	88.8	259.6	58.3	211.6
	Nov	47.8	93.3	49.8	99.1	51.5	90.6	28.6	88.5
	Dec	27.6	49.2	33.0	60.1	30.8	48.1	22.4	45.2
2	1 day-min	7.2	15.9	8.5	23.4	4.3	15.0	3.4	11.7
	3 day-min	7.5	17.1	8.5	23.9	4.3	16.8	3.4	12.3
	7 day-min	8.3	18.7	8.7	24.9	4.5	17.1	6.2	12.5
	30 day-min	9.2	20.6	9.7	27.5	7.7	17.7	9.8	15.9
	90 day-min	14.0	29.2	13.1	39.4	14.0	34.3	13.2	20.7
	1 day-max	3600.0	7660.0	4460.0	8807.5	3900.0	7760.0	1875.3	5007.5
	3 day-max	2943.3	5906.7	3172.5	6710.1	3170.0	6023.3	1446.3	3046.7
	7 day-max	1854.7	3571.4	2434.3	4310.3	1950.7	3571.4	901.9	1939.6
	30 day-max	837.1	1429.0	1223.4	1732.1	862.9	1204.6	444.4	825.7
	90 day-max	516.6	801.7	756.5	1078.8	577.7	697.1	309.6	521.0
	Base	0.029	0.081	0.029	0.077	0.023	0.073	0.040	0.100
3	Date of min	120.0	174.0	120.0	166.3	96.0	191.0	129.3	190.0
	Date of max	57.0	120.0	53.8	109.8	79.0	116.0	40.0	140.5
4	Low count	2.0	5.0	2.0	4.0	2.0	5.0	3.0	6.3
	High count	5.0	10.0	5.8	9.3	5.0	9.0	7.0	11.0
	Low duration	51.0	125.0	50.3	136.0	48.0	125.0	73.8	123.3
	High duration	74.0	115.0	73.5	107.3	75.0	113.0	70.3	116.0
5	Fall rate	−119.0	−58.4	−147.8	−85.9	−93.6	−59.9	−74.8	−31.8
	Rise rate	151.6	305.4	219.1	391.7	153.1	282.8	78.2	191.1
	Reversal	92.0	114.0	86.8	113.0	87.0	113.0	98.0	116.0

[a]For units see Table 2.

et al. [1997] suggested using existing flow records, preferably longer than 20 years, to define the natural, or less altered, ranges of variability in hydrologic regimes, it remains uncertain whether 20 years is sufficient for justifying the statistical validity. Despite that the flow records used herein are not very long, from the data shown in Table 3 and the results presented in section 4.2, we believe that these flow data are sufficient for demonstrating the interannual variability that is the major component to be incorporated in this study, at least to the extent the proposed framework can be used to demonstrate such possibility.

[18] The IHA target ranges may vary from year to year depending on the type of each year, thus the values of D_i and D_o so obtained would differ from those evaluated with the target ranges established using the data from all years. Because historical flow data are used in this study, no prediction of the water year type is needed. In practice, however, if the interannual variability is to be incorporated in the environmental flow schemes, the type of water year must be determined a priori using any real-time prediction techniques, which together with the uncertainty and risk associated with the real-time predictions are beyond the scope of this study and thus remain to be addressed in the future.

3.3. Intra-annual Flow Variability

[19] The monthly flows given in Table 1 clearly demonstrate the natural flow pattern at the Kaoping diversion weir. To maintain this kind of intra-annual flow variability, different sets of Q_{EF}^t are prescribed using three time-varying schemes, which include the semiannually, quarterly, and monthly varying schemes. For the semiannually varying scheme, different values of Q_{EF}^t are prescribed for the wet and dry seasons (i.e., May–October and November–April). For the quarterly varying scheme, different values of Q_{EF}^t are prescribed for the four quarters (i.e., February–April, May–July, August–October, and November–January); while for the monthly varying scheme, twelve Q_{EF}^t are specified for the different months. As such, a total of 36 Q_{EF}^t values are to be prescribed for the monthly varying scheme incorporating three types of water year, whereas only one Q_{EF} is to be specified for the flat line constant scheme incorporating neither the intra-annual nor the interannual flow variability.

3.4. Multiobjective Optimization

[20] As mentioned earlier, the operational goal of the Kaoping diversion weir seeks to meet both the ecosystem and human needs criteria, which can be expressed by

$$\mathrm{Min}\{D_o, SR\} \tag{6}$$

To tackle this multiobjective optimization problem, we employ the nondominated sorting genetic algorithm II (NSGA-II) [*Deb et al.*, 2002] to search the Pareto sets of Q_{EF}^t for various schemes. The NSGA-II belongs to the family of population-based evolutionary algorithms, which are widely recognized for their ability to find multiple

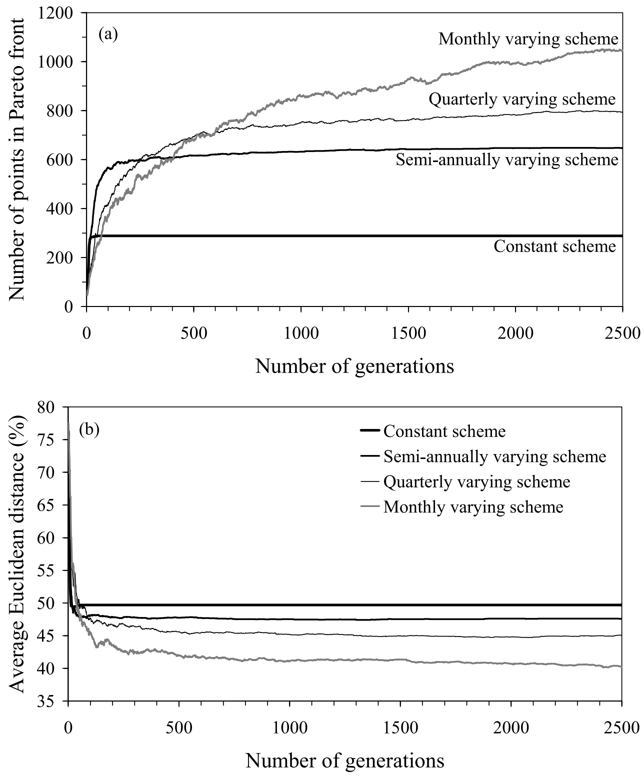

Figure 5. Evolutions of (a) number of points in the Pareto front and (b) average Euclidean distance with the number of generations. The interannual flow variability is not incorporated in these schemes.

Pareto-optimal solutions (i.e., the Pareto front) in a single simulation. The resulting relation between the conflicting objectives offers decision makers with the marginal trade-offs useful for selection of the preferred solutions [*Wu and Chou*, 2004]. The NSGA-II uses an elitist-preserving procedure to perform fast nondomination sorting. It also employs a crowding-comparison selection operator to maintain a good spread of the solutions. Since it was introduced, the NSGA-II has quickly become a popular tool for multiobjective optimization. Application examples can be found in work by *Reed et al.* [2003], *Prasad and Park* [2004], *Bekele and Nicklow* [2005], *Kapelan et al.* [2005], *Khu and Madsen* [2005], *Suen and Eheart* [2006], *Kim et al.* [2006], and *Yandamuri et al.* [2006], just to name a few among many others.

[21] The NSGA-II, along the line with simple GA, mimics the evolution processes of genes using the selection, crossover, and mutation operators to iteratively evolve a population toward the true Pareto-optimal front [*Deb*, 2001]. The NSGA-II starts with a random parent population of size n, whose members are ranked on the basis of the nondomination level. A simple GA is used to create an offspring population of equal size. A combined population of size $2n$ is formed. The NSGA-II algorithm is then used to choose from this combined population a new generation of parent population. The procedure is repeated until a stable Pareto front is obtained, which was confirmed in this study by the number of points in the Pareto front and the average Euclidean distance between the origin and the Pareto-optimal points. The population size must be specified according to the number of decision variables. For the monthly varying scheme incorporating the interannual flow variability (with 36 decision variables), a population size of 1,500 was used; for those less varying schemes with the numbers of decision variables <6, a population size of 1,000 was adopted; for the other schemes in between, a population size of 1,200 was employed. Typical values of 0.8 and 0.05 were used in this work for the crossover and mutation rates, respectively.

4. Results and Discussion

[22] The SPI approach, RVA, weir operation model, and NSGA-II are integrated into a multiobjective optimization framework for finding the Pareto-optimal solutions of various flow schemes. The environmental flow schemes considered here include those without incorporating the interannual variability (i.e., a constant scheme and three intra-annually varying schemes) and those incorporating the interannual variability (i.e., an intra-annually constant but interannually varying scheme, and three time-varying schemes incorporating both the intra-annual and interannual flow variability).

4.1. Pareto-Optimal Solutions Without Incorporating Interannual Flow Variability

[23] To investigate the effect of incorporating the intra-annual variability, four different schemes, including a constant and three time-varying (i.e., semiannually, quarterly, and monthly varying) schemes, are compared. The numbers of the Q_{EF}^t values to be specified for these schemes are 1, 2, 4, and 12, respectively. For each scheme, the Pareto sets of Q_{EF}^t were searched in a full range of flows (between 0 and the historical maximum 15,470 m^3/s) until a satisfactory convergence to the true Pareto front was achieved.

[24] Figure 5a reveals that 2,500 generations of NSGA-II simulations are needed for the monthly varying scheme to reach a reasonably stable number of points in the Pareto front, while the constant scheme plateaus much faster. The number of points in the Pareto front is greater for the scheme with a higher time-varying frequency; that is, more Pareto-optimal solutions are available for the scheme with a greater number of decision variables. The convergence of the Pareto-optimal solutions is further confirmed in Figure 5b, where the average Euclidean distance is smaller for the scheme with a higher time-varying frequency. Such a trend is clearly demonstrated in Figure 6a where the proximity of the Pareto front to the origin of the objective space is consistently enhanced when the time-varying frequency is increased. The results indicate that by incorporating more of the intra-annual variability, the time-varying flow schemes promote both the ecosystem and human needs fitness.

[25] Since all the solutions on the Pareto front are equally good, here we arbitrarily select three points from the Pareto front just to see how the outcomes such as D_o, SR, and the Euclidean distance L of the individual point are affected by the flow schemes (Table 4). The three selected points include the upper left (UL) and lower right (LR) ends, and a postoptimal solution defined as the Pareto-optimal solution with a minimal value of L [*Deb*, 2001] (shown in the inset of Figure 6a). Note that this postoptimal solution is not the "best" solution but simply a Pareto-optimal point that is closest to the origin. The UL end is a Pareto-optimal

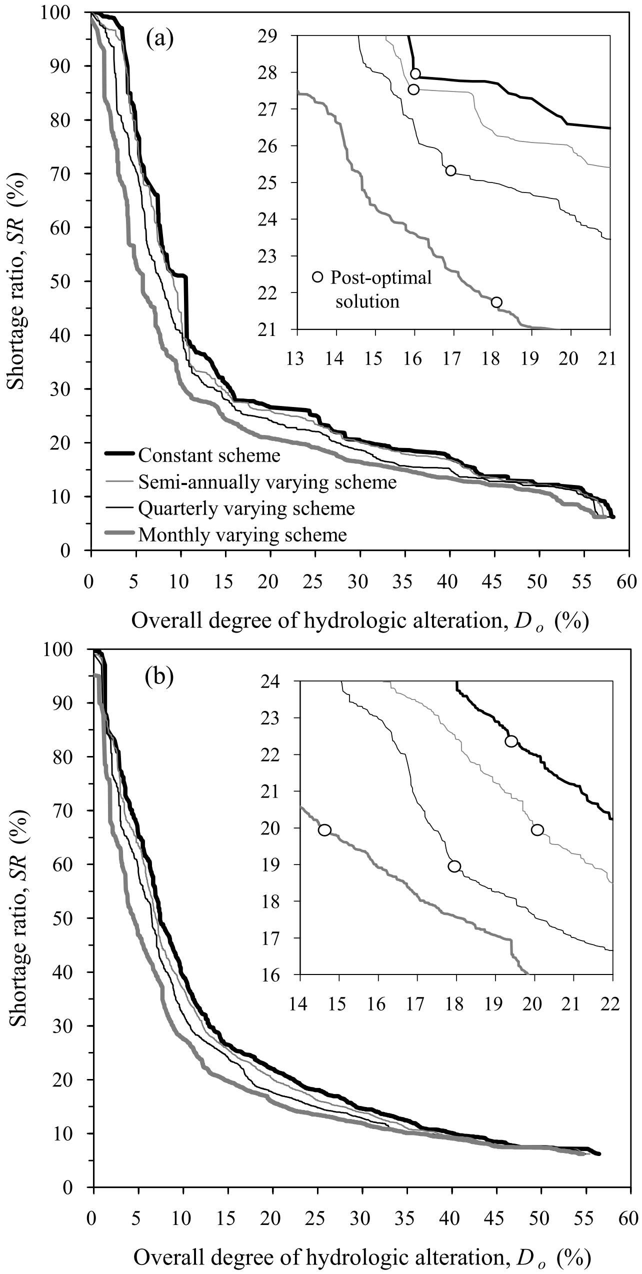

Figure 6. Pareto fronts of various flow schemes (a) without and (b) with incorporating the interannual variability. The inset is a close-up of the graph near the postoptimal solutions that are defined as the Pareto-optimal points closest to the origin.

solution most favorable to the ecosystem needs (i.e., minimal D_o = 0) but least favorable to the human needs; whereas the LR end is the one most favorable to the human needs (i.e., minimal SR = 6.2%) but least favorable to the ecosystem needs. The outcomes associated with the UL and LR ends of the constant scheme, semiannually and quarterly varying schemes are identical because the UL end corresponds to zero diversions and the LR end corresponds to zero environmental flows. The outcomes associated with the monthly varying scheme deviate slightly from the preceding ones because nonzero values may be specified in some months, which can only be achieved by the monthly varying scheme. For example, at the LR end the monthly varying scheme may specify 0.19 and 0.98 m^3/s to the values of Q_{EF}^t in August and September without sacrificing the minimal value of SR. By adapting the environmental flows more closely to the natural flows, the monthly varying scheme results in better outcomes at the UL and LR ends. Moreover, the value of L of the postoptimal solution reduces from 32.2 to 28.2% as the flow scheme is modified from a constant to monthly varying one, which is, however, more attributed to the reduction in SR because of its greater range (i.e., 6~100% for SR and 0~58% for D_o).

4.2. Pareto-Optimal Solutions Incorporating Interannual Flow Variability

[26] In this section we proceed to investigate the Pareto-optimal solutions of those schemes that incorporate the interannual flow variability, which include an intra-annually constant and three time-varying (i.e., semiannually, quarterly, and monthly varying) schemes. The interannual flow variability is defined here by three types of water year, thus the numbers of the Q_{EF}^t values to be specified for these schemes are 3, 6, 12, and 36, respectively. Evaluations of D_o were based on the IHA target ranges established for the three types of water year. For each flow scheme, the Pareto sets of Q_{EF}^t for the wet, normal, and dry years were separately searched in the full range of flows until a satisfactory convergence to the true Pareto front was achieved.

[27] Figure 7 reveals that these interannually varying flow schemes need more generations to reach the reasonably stable state. Nevertheless, similar trends are observed in Figures 5 and 7 where the number of points in the Pareto front is greater for the scheme with a higher time-varying frequency, while the average Euclidean distance is smaller for such a scheme. Figure 6b reveals that the proximity of the Pareto front to the origin is not only enhanced by the increasing time-varying frequency, but also enhanced by incorporating the interannual variability in the flow schemes. To demonstrate this more clearly, we show in Figure 8 (see gray solid lines) four pairs of Pareto fronts resulting from the different flow schemes. It is revealed that, regardless of the scheme used, the entire Pareto front shifts toward the origin as the interannual variability is incorporated in the flow schemes, indicating the possibility of further promoting both the ecosystem and human needs fitness. The result also implies that the merit of incorporating the interannual flow variability may be superimposed on that of incorporating only the intra-annual variability. As an additional note, herein different environmental flow prescriptions are used in the three types of water year, which is a reasonable strategy because otherwise simultaneous promotion of the ecosystem and human needs fitness would become impossible. However, to implement different environmental flow prescriptions would, in practice, require a real-time prediction of the water year type.

[28] The result demonstrated here is not too surprising since the year-type IHA targets are by definition easier to achieve. A similar result would have been found if the human demands were reduced in dry years and increased in wet years. A less intuitive exercise, however, would be to increase human demands in dry years and decrease them in wet years. This might occur in situations where other sources of water fail during drought, thereby increasing reliance on the Kaoping weir, but less water is needed in

Table 4. Outcomes Associated With the Three Selected Pareto-Optimal Solutions for the Flow Schemes Without Incorporating the Interannual Variability[a]

		Constant Scheme			Time-Varying Schemes: Semiannually			Quarterly			Monthly		
Search Range	Outcome	UL End	LR End	Postoptimal	UL End	LR End	Postoptimal	UL End	LR End	Postoptimal	UL End	LR End	Postoptimal
Full	D_o (%)	0	58.2	16.0	0	58.2	15.9	0	58.2	16.9	0	57.3	18.2
	SR (%)	100	6.2	27.9	100	6.2	27.6	100	6.2	25.3	98.7	6.2	21.5
	L (%)	100	58.6	32.2	100	58.6	31.8	100	58.6	30.4	98.7	57.7	28.2
Limited	D_o (%)	**9.4**	58.2	16.0	**9.0**	58.2	15.9	**8.8**	58.2	16.9	**8.9**	57.3	18.2
	SR (%)	**51.2**	6.2	27.9	**51.2**	6.2	27.6	**50.7**	6.2	25.3	**39.4**	6.2	21.5
	L (%)	**52.1**	58.6	32.2	**52.0**	58.6	31.8	**51.4**	58.6	30.4	**40.4**	57.7	28.2

[a]The upper left (UL) end is most favorable to the ecosystem needs but least favorable to the human needs; the lower-right (LR) end is most favorable to the human needs but least favorable to the ecosystem needs; the postoptimal solution is a Pareto-optimal point closest to the origin. (The results obtained with the full and limited search ranges are shown.)

wet years because of these same alternative sources. Under this scenario, it is not obvious what the outcome would be, as it would depend on the magnitude of human demands in different types of year.

[29] Again, we use the UL and LR ends of the Pareto fronts and the postoptimal solutions with minimal values of L (Figure 6b) to demonstrate how the outcomes (i.e., D_o, SR, and L) are affected by the flow schemes. The results shown in Table 5 are consistent with those shown in Table 4; that is, the UL ends of the Pareto fronts are associated with the best fitness to the ecosystem needs (minimal D_o), whereas the LR ends are most favorable to the human needs (minimal SR). The values of SR associated with the UL ends and the values of D_o associated with the LR ends are consistently smaller than the corresponding values shown in Table 4, and decline with the increasing time-varying frequency. Although 3 out of 4 values of D_o associated with the postoptimal solutions are greater than the corresponding

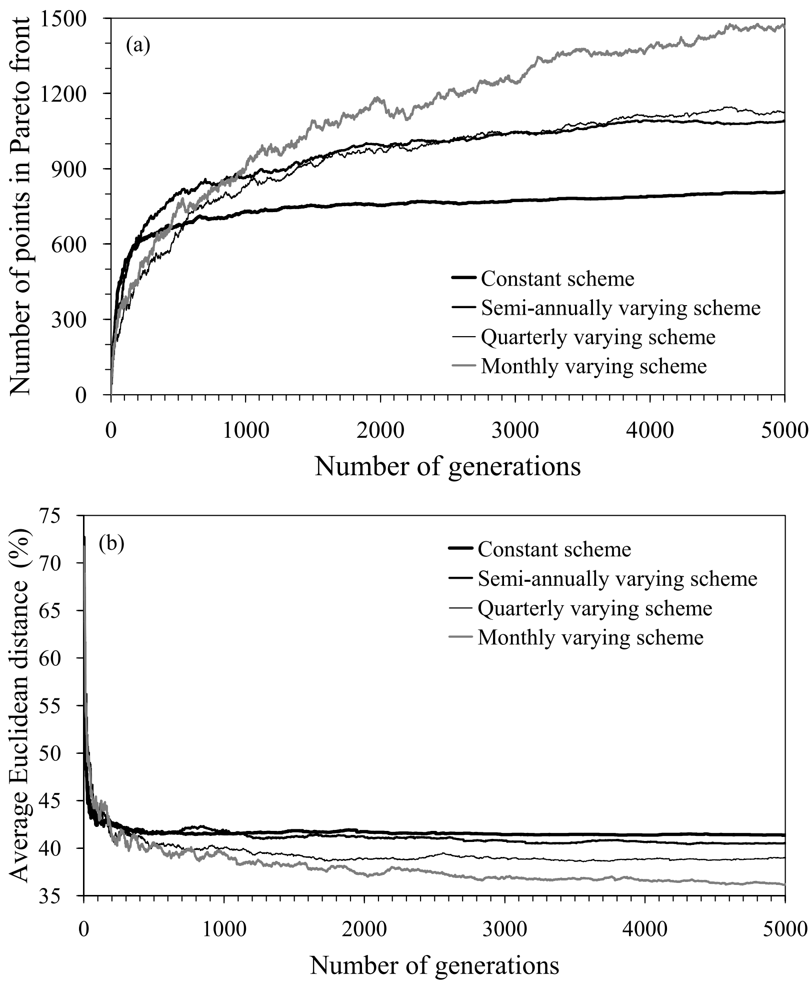

Figure 7. Evolutions of (a) number of points in the Pareto front and (b) average Euclidean distance with the number of generations. The interannual flow variability is incorporated in these schemes.

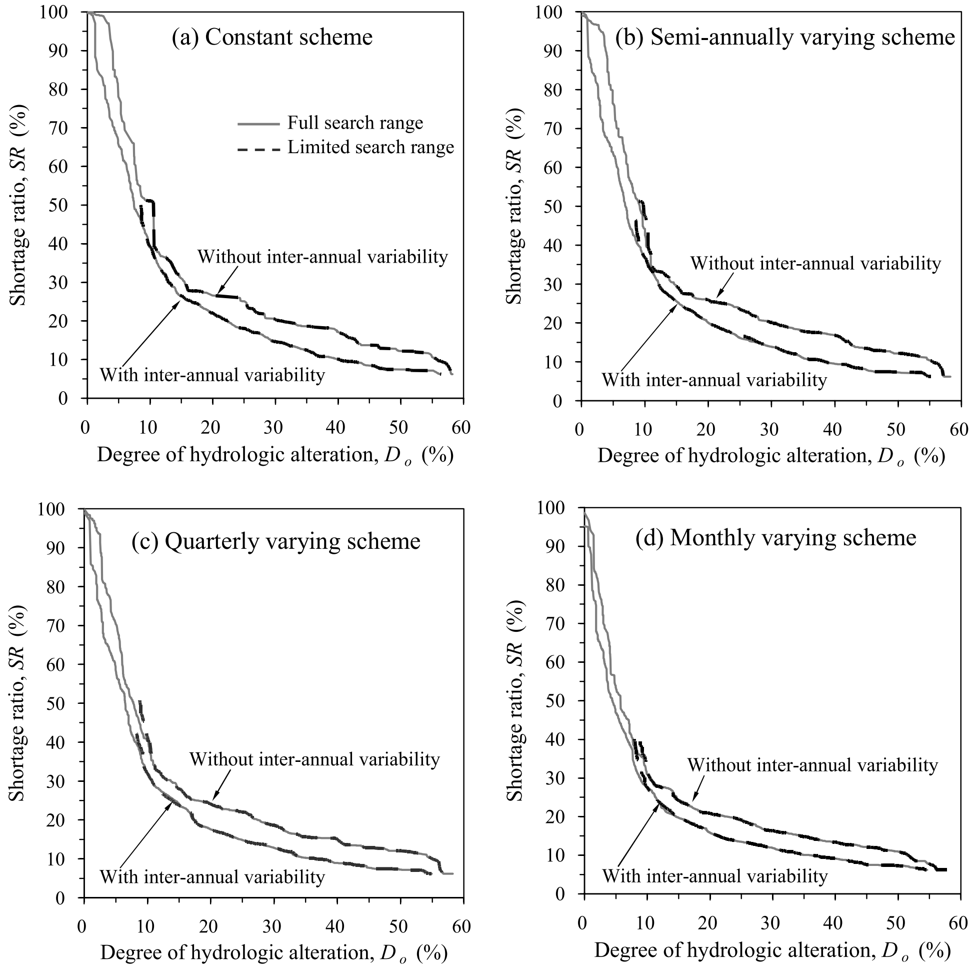

Figure 8. Pareto fronts of the individual flow schemes with and without incorporating the interannual variability. Gray solid lines are the results searched with a full range of flows; dashed lines are those searched with a limited range of flows.

values shown in Table 4, the reductions in *SR* are much greater and thus more dominant in affecting the values of *L*, as described in the previous section.

4.3. Pareto-Optimal Solutions With a Limited Search Range

[30] The Pareto-optimal solutions discussed above were searched in the full range of flows between 0 and the historical maximum 15,470 m^3/s. Such high flows are, however, extreme events and impractical for the weir operations. Since the IHA target ranges used herein are bracketed by their 25th- and 75th-percentile values, the environmental flow prescriptions may possibly be searched in a range of the regular flows without degrading too much of the outcomes. *Shiau and Wu* [2006] have pointed out that a constant Q_{EF}^t = 93 m^3/s for the Kaoping weir operation would make all the IHA classified as low alteration because the environmental flows are given a higher priority than the

Table 5. Outcomes Associated With the Three Selected Pareto-Optimal Solutions for the Flow Schemes Incorporating the Interannual Variability[a]

					Time-Varying Schemes								
		Constant Scheme			Semiannually			Quarterly			Monthly		
Search Range	Outcome	UL End	LR End	Postoptimal	UL End	LR End	Postoptimal	UL End	LR End	Postoptimal	UL End	LR End	Postoptimal
Full	D_o (%)	0	56.4	19.4	0	55.4	20.1	0	54.9	18.0	0	54.6	16.0
	SR (%)	99.7	6.2	22.3	99.0	6.2	19.9	99.0	6.2	18.8	95.2	6.2	18.9
	L (%)	99.7	56.8	29.6	99.0	55.7	28.3	99.0	55.3	26.1	95.2	55.0	24.8
Limited	D_o (%)	**8.5**	56.4	19.4	**8.5**	55.4	20.1	**8.3**	54.9	18.0	**7.8**	54.6	16.0
	SR (%)	**50.0**	6.2	22.3	**46.4**	6.2	19.9	**42.2**	6.2	18.8	**39.8**	6.2	18.9
	L (%)	**50.7**	56.8	29.6	**47.2**	55.7	28.3	**43.0**	55.3	26.1	**40.6**	55.0	24.8

[a]The upper left (UL) end is most favorable to the ecosystem needs but least favorable to the human needs; the lower-right (LR) end is most favorable to the human needs but least favorable to the ecosystem needs; the postoptimal solution is a Pareto-optimal point closest to the origin. (The results obtained with the full and limited search ranges are shown.)

flow diversions, as noted earlier. Thus, in this section we search the Pareto sets of Q^t_{EF} in a range of flows between 0 and 100 m^3/s, which excludes 42% of the daily flows, to see how a limited search range would affect the Pareto-optimal solutions of various flow schemes.

[31] The Pareto fronts resulting from the limited search range are shown in Figure 8 using the dashed lines. It is revealed that, regardless of the flow schemes used, the limited-range Pareto front deviates from the corresponding full-range Pareto front only in a small portion at the UL end, where the limited-range Pareto front is slightly inferior to the full-range one because of the imposed upper bound. The remaining part of the limited-range Pareto front, however, coincides with the full-range Pareto front, indicating that the Pareto sets of Q^t_{EF} in the full-range front are mostly composed of the regular flows. The outcomes associated with the limited-range Pareto fronts are also shown in Tables 4 and 5, respectively for the flow schemes ''without'' and ''with'' the interannual variability incorporated. The results reveal that only the outcomes associated with the UL ends of the limited-range Pareto fronts are affected (shown in the boldface), while the other outcomes remain unaffected.

[32] In summary, the Pareto-optimal solutions resulting from a regular flow range replicate satisfactorily the full-range Pareto front, but eliminate the portion associated with extreme flows that are impractical for the weir operations. Because the cost of the full-range search is relatively high, especially for the flow schemes that vary both intra-annually and interannually, an important implication of our result is that the limited-range Pareto front may well be used as a surrogate of the full-range Pareto front, in case that an appropriate range of flows can be defined by some preliminary analyses.

5. Conclusions

[33] We present in this work an RVA-based multiobjective optimization framework to find the Pareto-optimal solutions for the environmental flow schemes that incorporate the intra-annual and interannual variability of the natural flow regime. Three subjects are pursued herein. First, we employ the time-varying schemes to incorporate the intra-annual variability in the environmental flow prescriptions. The Pareto-optimal fronts of the time-varying schemes demonstrate a simultaneous promotion of the ecosystem and human needs fitness. Second, the interannual variability is incorporated in the environmental flow prescriptions using different IHA targets established for the wet, normal, and dry years. The results reveal that incorporating the interannual flow variability would further promote both the ecosystem and human needs fitness. The merit of incorporating the interannual flow variability may be superimposed on the merit of incorporating only the intra-annual flow variability. Third, we demonstrate that the Pareto-optimal solutions searched with a limited range of flows replicate satisfactorily those obtained with a full search range. The limited-range Pareto front may well be used as a surrogate of the full-range one if feasible prescriptions are to be found among the regular flows.

[34] The purpose of this study is to demonstrate the effects on the ecosystem and human needs fitness of incorporating the intra-annual and interannual variability in the environmental flow schemes. The multiobjective optimization framework and weir operation simulations presented here are solely for such scope but not for the planning purpose. To include a component for real-time predictions of the water year type is essential for the proposed framework to be used as a planning tool, thus remains as a topic for future studies.

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