

Interval number fuzzy linear programming for climate change impact assessments of reservoir active storage

Ching-Pin Tung · Nien-Ming Hong ·
Ming-hsu Li

Received: 8 September 2009 / Accepted: 7 October 2009 / Published online: 21 October 2009
© Springer-Verlag 2009

Abstract The major uncertainty in the climate change impact study inherits from applying the predictions of General Circulation Models (GCMs). Different results might be obtained by using various GCMs' predictions, which causes difficulties on the decision making of water resources management. This study proposed an integrated hydrological simulations and optimization framework, consisting of a fuzzy linear programming model with interval numbers, a streamflow simulation model, and agricultural water demand projections, to evaluate the impacts of climate change on reservoir active storage. The reservoir inflows are simulated by the WatBal model, while agricultural water demands are predicted based on the projected change of potential evapotranspiration. Inflows and water demands are used to formulate an interval number fuzzy linear programming model. Fuzzy relationships are used to describe tolerable deficits of water resources, and the interval number is employed to indicate ranges of possible inflows and water demands. This systematic framework is applied to study the Tsengwen reservoir watershed to provide an optimal interval of active storage. The results further

indicate the higher tolerable deficit, the smaller difference between superior and inferior active storage.

Keywords Water resources · Uncertainty · Climatic change · Global warming

Introduction

Increasing atmospheric greenhouse gases is known to be the cause of global warming which in turn induces the changes of precipitation and temperature. The impacts of climate change on water resources have been the focuses of many hydrometeorological studies. For example, the most widely reported effects on streamflows are due to the changes of precipitation and temperature (Gleick 1987; Tung and Haith 1995; Tung 2001). Climate change could also affect water demand, especially agricultural water requirements (McCabe et al. 1990; Tung and Haith 1998). Since the requirement of water storage is determined by both streamflows and water demands, the evaluation of future reservoir storage should take the influences of climate change into consideration.

There are numerous uncertainties should be considered in the impact studies of climate change. Most impact studies rely on the climate change scenarios, which can be derived from the predictions of General Circulation Models (GCMs). More than one GCMs predictions are often used to avoid the bias caused by a single model. Due to the complexity of the interacted processes between global warming and the climate system, different GCMs often have different predictions. The major uncertainties of the impact studies are essentially inherited from the discrepancies among various GCMs' predictions, which increase the difficulties for the planning of reservoir storage. Others might be caused by the

C.-P. Tung
Department of Bioenvironmental Systems Engineering,
National Taiwan University, No. 1, Sec. 4, Roosevelt Rd.,
Taipei, Taiwan, ROC
e-mail: cptung@ntu.edu.tw

N.-M. Hong (✉)
Department of Environmental Resources Management, Overseas
Chinese University, Overseas Chinese Institute of Technology,
100, Chiao Kwang Rd, 407 Taichung, Taiwan, ROC
e-mail: hong@ocu.edu.tw

M. Li
Institute of Hydrological Sciences, National Central University,
No.300, Zhongda Rd., Taoyuan, Taiwan, ROC
e-mail: mli@ncu.edu.tw

downscaling techniques employed on handling spatial and temporal scale issues that are not the focus of this study.

Linear programming (LP) model is commonly applied for water resources planning, but the algorithm itself is lack of ability to deal with such uncertainties. The LP model is to maximize or minimize a linear function with linear constraints. Typically, the mean values of coefficients are used for a model. Thus, it is unable to reflect the uncertainty of a system. Linear programming with chance constrained (Loucks et al. 1981) was developed to deal with such uncertainty. However, extra efforts are needed to analyze the probability distribution of the concerned information.

Interval Number Linear Programming (INLP) was introduced to solve for the best (superior) and the worst (inferior) optimal solutions (Tong 1994) from all possible combinations of interval coefficients and the right hand side constants. Interval numbers reflect the maximum and minimum predictions, and both of them are with the same properties. By maximizing the minimum value of membership functions among the objective and constraints, fuzzy linear programming (FLP) model (Negoita and Sularia 1976) has been applied to many research areas. Fuzzy concept could help us to evaluate the tolerance because the optimal solution may be overestimated while both maximum and minimum predictions are used without fuzzy sets.

A fuzzy linear programming model with interval numbers was proposed in this study, named as Interval Number Fuzzy Linear Programming (INFLP) model. The INFLP model was applied to deal with the uncertainty of climate change impacts caused by using different GCMs. Reservoir active storage was determined to meet water demands according to upstream inflows. Water demands and inflows under climate change with uncertainties taken into account can be evaluated. The projected change of active storage presents the

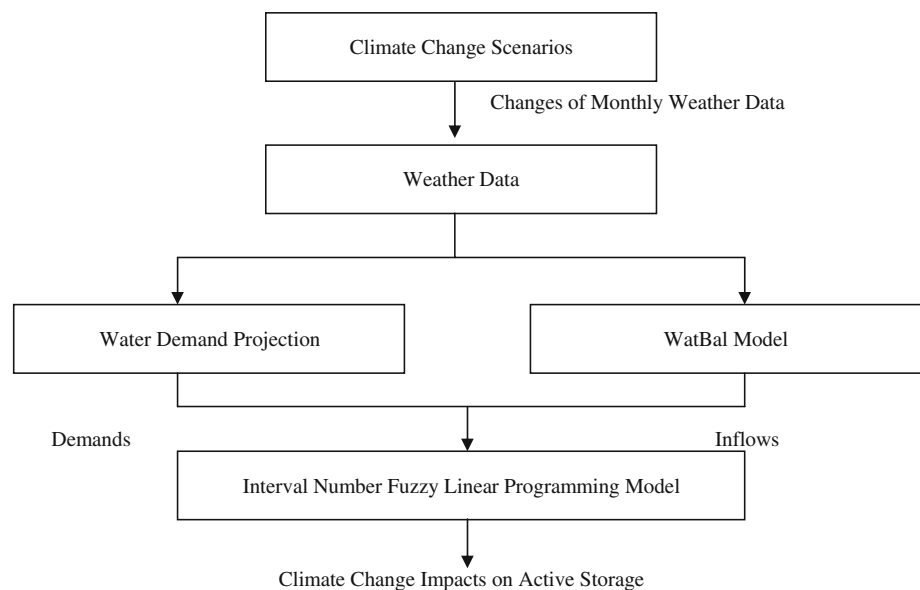
effects of climate change. Typically, the probability distributions are used to resolve the inflow characteristics by most research. But the shortcoming is that the probability distributions are not well defined in the case of climate change. Instead, interval numbers can be applied to indicate possible range of inflows and water demand variations. On the other hand, the level of satisfaction of water supply is defined subjective to the fuzzy membership function. The purpose of this study is to propose a systematic framework incorporating the INFLP model with hydrological simulations for water resources planning under the conditions of climate change.

Methodology

A simulation/optimization framework is proposed for evaluating the impacts of climate change on the reservoir active storage that depends on water demands and inflows. Reservoir inflows were simulated by using the WatBal model, and water demands were evaluated for different climatic change conditions. And, the active storage was minimized by the use of INFLP model.

Fuzzy sets and interval numbers were used to describe the satisfaction of water supply and the uncertainties of water demands and inflows, respectively. Little deficit of the unsatisfied water supply is considered to be tolerable and described by a fuzzy set. On the other hand, different GCMs may predict different temperature and precipitation fields and thus result in different forecasted inflows and water demands. Interval numbers were used to describe the ranges of inflow and water demand variations that predicted based on different GCMs' scenarios. Finally, an INFLP model was formulated for the planning of the reservoir capacity under the effects of predicted climate change.

Fig. 1 The flow chart of this study



The flowchart of this study is shown in Fig. 1. Climate scenarios were derived from historical weather records and GCMs’ outputs, and then current and future weather data for simulation were generated based on these scenarios. The future weather data were used to predict future water demands. Meanwhile, the WatBal model was used to simulate the inflows for the same climate change conditions. After modifying water demands and simulating inflows, an INFLP model was formulated to determine the optimal active storage.

Simulation model

The WatBal model (Yates 1996), based on the study of Kaczmarek (1993), was used to simulate monthly streamflows in this study. The WatBal is a conceptual and lumped water balance model. It required the input of precipitation and temperature. The output fields of the model included evapotranspiration and streamflow. Surface runoff, subsurface runoff, and evapotranspiration are presented as the functions of relative soil water storage. The differential equation used to describe water balance of soil moisture is as follow:

$$S_{\max} \frac{dz}{dt} = P_{\text{eff}}(1 - \beta) - R_s - R_{\text{ss}} - R_b - E_v \tag{1}$$

where S_{\max} is maximum catchments water holding capacity; z is relative soil water storage; P_{eff} is effective rainfall, and $\beta \cdot P_{\text{eff}}$ is direct runoff (R_d); R_s is the surface runoff; The R_d is presented as the direct runoff which is no relationship with soil water storage. The R_s is quickly response of rainfall as a function of soil water storage. R_{ss} is subsurface runoff; R_b is base flow; and E_v is evapotranspiration. Total runoff, for each time step, is the sum of the four components:

$$R_t = R_d + R_s + R_{\text{ss}} + R_b. \tag{2}$$

Surface runoff is defined as follow:

$$R_s = \text{Max}[0, z^\varepsilon(P_{\text{eff}} - R_d)]. \tag{3}$$

In the above equation, ε is a constant, surface runoff is approaching zero for an infinitesimal values of relative storage. R_{ss} can be defined as a nonlinear reservoir system as follow:

$$R_{\text{ss}} = \alpha z^\gamma, \tag{4}$$

where α and γ are constant parameters in Eq. 4. Evapotranspiration is a function of potential evapotranspiration (PET) and the relative catchment soil water storage state. A number of expressions have been given to describe evapotranspiration as a function of soil moisture state (Kaczmarek and Krasuski 1991). The control equation for evapotranspiration is defined as follows:

$$E_v = \text{PET} \times z. \tag{5}$$

The INFLP model

Different GCMs predict different changes of precipitation and temperature at the same time period, and thus result in different forecasted values for inflows and water demands. The interval numbers are used to describe the ranges of forecasted inflows and water demands by different GCMs. With this uncertain information, an INFLP model is formulated as the M1 model.

M1 model

$$\begin{aligned} & \text{Min } K_a \\ & \text{S.T.} \\ & S_{13,y} = S_{1,y+1} \quad y = 1, \dots, n - 1 \\ & S_{t,y} - S_{t+1,y} \gtrsim \\ & [y_{t,y}^-, y_{t,y}^+] - [q_{t,y}^-, q_{t,y}^+] \quad t = 1, \dots, 12 \quad y = 1, \dots, n \\ & K_a \geq S_{t,y} \quad t = 1, \dots, 12 \quad y = 1, \dots, n \\ & \text{all variables} \geq 0 \end{aligned}$$

where interval numbers, $[y_{t,y}^-, y_{t,y}^+]$ and $[q_{t,y}^-, q_{t,y}^+]$, present the range of water demands and inflows respectively, derived from the simulation models and water demand projection. The $y_{t,y}^-$ is the minimal value of inflows among all GCMs’ scenarios at month t of year y . K_a is the active storage for planning and $S_{t,y}$ is the storage of reservoir. The symbol “ \gtrsim ” is used to describe fuzzy relationship.

The M1 model is then divided into two submodels, which are based on the principle of interval number linear programming (Tong 1994), denoted as M11 model and M12 model. The relationship between the optimum and feasible regions is the larger the feasible region, the better the optimal solution. M11 model could produce the best optimum solution (i.e., the superior K_a , denoted as $K_{a,\text{min}}$) with the largest feasible region. On the other hand, the M12 model could find the worst optimum solution (i.e., the inferior K_a , denoted as $K_{a,\text{max}}$) with the smallest feasible region.

M11 model	M12 model
$\text{Min } K_a$	$\text{Min } K_a$
<i>Subject to:</i>	<i>Subject to</i>
$S_{13,y} = S_{1,y+1}$	$S_{13,y} = S_{1,y+1}$
$S_{t,y} - S_{t+1,y} \gtrsim y_{t,y}^- - q_{t,y}^+$	$S_{t,y} - S_{t+1,y} \gtrsim y_{t,y}^+ - q_{t,y}^-$
$K_a \geq S_{t,y}$ all variables ≥ 0	$K_a \geq S_{t,y}$ all variables ≥ 0

Because little deficit of water supply is tolerable, the capacity of active storage and the relationship between storage and supply could be regarded as content with the fuzzy relationship. Zadeh (1965) proposed a membership function to characterize fuzzy sets. Different levels of designed service can be characterized into a set which service is acceptable with different satisfaction. If designed service (X_t) has to be not less than requirement (x_t), i.e., $X_t > x_t$, an acceptable set can be described by a membership function as Eq. 6. The value of membership function is denoted as μ_x . Equation 6 explains that when service (X_t) is larger than or equal to the goal (x_t), the service is 100% belong to the acceptable set, which the value of membership function is 1. When the designed service is less than a tolerant minimum level ($x_t - dx_t$), it is not belong to the acceptable sets, and thus the value of membership function is 0. Otherwise, the service, between ($x_t - dx_t$) and (x_t), is designed linearly as the decrease of service.

$$u_x = \begin{cases} 1 & \text{if } X_t \geq x_t \\ 1 - \frac{x_t - X_t}{dx_t} & \text{if } x_t - dx_t \leq X_t < x_t \\ 0 & \text{if } X_t < x_t - dx_t \end{cases} \quad (6)$$

Therefore, the objective function and the second constraint in the M1 model could be described by a fuzzy membership function shown as Fig. 2. Then, the

M21 model	M22 model
$Max \lambda$ Subject to $\lambda \leq 1 - \frac{K_a^{sup}}{K_{a,min}}$ $\lambda \leq 1 - \frac{[y_t^- - q_t^+] - (S_t - S_{t+1})}{dy_t}$ $K_a^{sup} \geq S_{t,y}$ all variables ≥ 0	$Max \lambda$ Subject to $\lambda \leq 1 - \frac{K_a^{inf}}{K_{a,max}}$ $\lambda \leq 1 - \frac{[y_t^+ - q_t^-] - (S_t - S_{t+1})}{dy_t}$ $K_a^{inf} \geq S_{t,y}$ all variables ≥ 0

INFLP can be formulated as the M21 model and the M22 model as follows.

where $K_{a,min}$ and $K_{a,max}$ can be derived from the M11 model and the M12 model without considering fuzzy relationships, respectively. The denominator, dy_t , is the tolerable deficits. Then, different superior and inferior active storages, K_a^{sup} and K_a^{inf} , can be determined when different levels of tolerable deficits are given.

Experiment design

The water supply system of the Tsengwen reservoir, located on the Tsengwen creek, Taiwan, was chosen as the study site. The predictions of the CCCM (Canadian Center for Climate Modeling) GFDL (Geophysical Fluid Dynamics Laboratory), and GISS (Goddard Institute for Space Studies) models were used to derive climate change scenarios.

Descriptions of study site

The area of the Tsengwen reservoir watershed is 489 km². The average inflow is 37.3 cm. About 85% of annual streamflows are recorded in the typhoon season, May through October. Historical records show that the maximum 3-day inflow is 574.2 million m³. The reservoir is designed for agricultural, industrial, and domestic water usage. Its water supply goals are shown in Table 1. The annual demands of the agriculture, industry, and domestics usage are about 900 million m³ (86%), 27 million m³ (3%), and 120 million m³ (11%), respectively.

Climate change scenarios

The impact of climate change on water resources was evaluated using three climate change scenarios derived from the predictions of equilibrium experiments from three GCMs, CCCM, GFDL, and GISS. The values of monthly

Fig. 2 Membership functions of the objective function and constraints

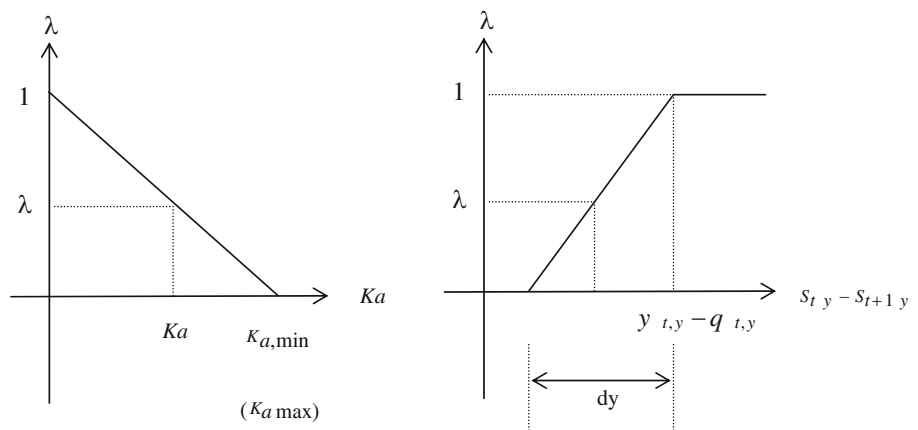


Table 1 Water supply goals of the Tsengwen reservoir for different users (10⁴ m³)

Month	Agricultural	Industrial	Domestic	Summary
1	2,730	270	1,100	4,100
2	11,490	240	1,100	12,830
3	8,480	270	1,000	9,750
4	10,580	250	1,000	11,830
5	6,140	240	1,000	7,380
6	8,320	190	1,000	9,520
7	10,580	200	900	11,680
8	7,980	200	800	8,980
9	8,650	200	800	9,640
10	7,950	200	1,100	9,250
11	3,290	190	1,100	4,580
12	3,810	250	1,100	5,160
Annual	90,000	2,700	12,000	104,700

mean temperature and precipitation under 1 × CO₂ and 2 × CO₂ were taken from the nearest grid points, which the 1 × CO₂ denotes normal atmospheric CO₂ concentration and the 2 × CO₂ means the doubling atmospheric CO₂ concentration. The predicted change of temperature of a watershed was assumed to be the same as the difference of temperatures between 2 × CO₂ and 1 × CO₂ conditions (Tung and Haith 1995; Tung 2001). The change of precipitation was considered as a fraction of precipitation in 2 × CO₂ climate condition to that in 1 × CO₂ climate condition. The relationships are given as follows.

$$\mu'_{mT} = \mu_{mT} + (\mu_{mT,2 \times CO_2} - \mu_{mT,1 \times CO_2}), \tag{7}$$

$$\mu'_{mP} = \mu_{mP} \times (\mu_{mP,2 \times CO_2} / \mu_{mP,1 \times CO_2}), \tag{8}$$

where μ_{mT} and μ'_{mT} are current and future monthly mean temperature (°C), $\mu_{mT,1 \times CO_2}$ and $\mu_{mT,2 \times CO_2}$ are simulated monthly mean temperatures (°C) under 1 × CO₂ and 2 × CO₂ conditions; μ_{mP} and μ'_{mP} are current and future monthly mean precipitation (cm), $\mu_{mP,1 \times CO_2}$ and $\mu_{mP,2 \times CO_2}$ are simulated monthly mean precipitation (cm) under 1 × CO₂ and 2 × CO₂ conditions. The predictions of the GCMs (1995 version) were downloaded from US Country Studies Program in the NCAR ftp site (<ftp://ncar.data.ucar.edu/pub>).

Design of agricultural water demand

The changes of agricultural water demands due to climate change were considered. The current demand is a designed goal under current climate, while the future demand includes the impacts on potential evapotranspiration caused by climate change. It is assumed that the change of agricultural water demand is proportional to the change of

potential evapotranspiration. The monthly agricultural water demand was described as:

$$D'_{a,m} = D_{a,m} \times \frac{PET'_m}{PET_m} \tag{9}$$

where PET_m and PET'_m are potential evapotranspiration estimated under 1 × CO₂ and 2 × CO₂, respectively, and $D_{a,m}$ and $D'_{a,m}$ are agricultural water demands under these two climate conditions, respectively. The effect of change of rainfall on agricultural water demand is not considered in the study.

Results

The results of calibrating and validating the WatBal model, simulated inflows for different climate scenarios and optimized active storage for climate change are described here.

Calibration and validation of the WatBal model

For determining the parameters, β , ε and α , in the WatBal model, the monthly rainfall records from 1974 to 1978 are used. The correlation coefficient that calculated between observed and simulated inflows is 0.97. Table 2 shows the calibrated parameters of the WatBal model. Further the records from 1979 to 1983 are used to validate these parameters. The correlation coefficient is about 0.93. The simulated and observed monthly streamflow hydrographs are shown in Fig. 3. The WatBal model is capable to simulate the inflows. The calibrated parameters were assumed to be constant and will be applied to simulate possible inflows for future climate conditions.

Impacts on streamflows

Streamflows were simulated under current and three different future climate scenarios. The results were given in Table 3. The maximum and minimum changes of streamflows for each month among these climate change scenarios are shown. It is noted that wet season inflows (from May to October) are increased by the range of 11–28% and a maximum decrease of about 8% is found at the dry season (from November to April). The change of monthly temperature is shown in Table 4.

The results of different GCMs are not consistent. For example, the changes of inflow in Jun are 40, −4.7, and

Table 2 Parameters of calibration in WatBal

S_{max}	ξ	α	β	γ
427.5 mm	0.525	1.0	0.0	2

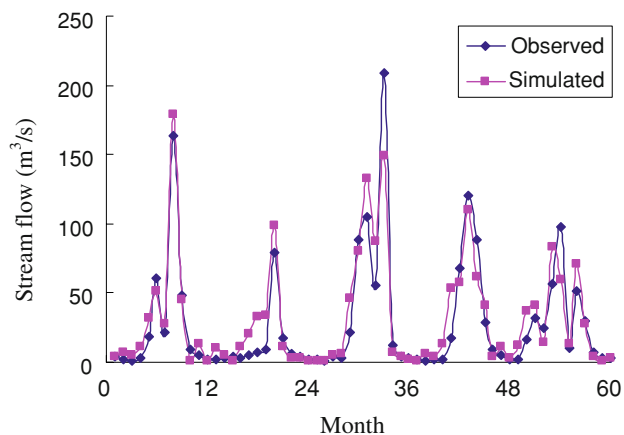


Fig. 3 The observed and simulated mean monthly flows of the Tsengwen Reservoir watershed—validation

54% from the CCCM, GFDL, and GISS scenarios, respectively. The highest change of inflow is from the GISS scenario, and the lowest is from the GFDL scenario. But in August the highest change of inflow is from the GFDL scenario, and the lowest is from the CCCM scenario. The maximum and minimum inflows are chosen from all GCMs. The inflows increase from August to October. In other months, the minimum change of inflows is negative and the maximum change is positive.

The abovementioned variations of projected inflows are caused by different climate change scenarios. The inflow increasing from August to October (wet season) also infers

that when possessing overflows, reservoirs could lose the ability to prevent flood. Because the inflows decrease in the dry period, the deficit situation might be a serious problem for the allocation of water resources under the climate change conditions. Based on the above discussion, setting up strategies to deal with these predicaments in advance is crucial.

Impacts on agricultural water demand

Using the Hamon’s equation (1961), the potential evapotranspiration (*PET*) was estimated for both current and future climates. The ratio of future agricultural water demand to the current one was assumed the same as the ratio of the future *PET* to the current *PET*. The results were shown in Fig. 4. Among all three scenarios, the maximum and minimum *PET* increments are 32 to 10%, respectively. The increments occur in both wet and dry periods. This result indicated that water demands were raised under the influence of climate change, and hence more inflows were needed. According to the results of inflow decrease in the dry period under the same climate change conditions, it would be a difficult task to fulfill the requirement of water demand. Therefore, it is important to take appropriate precautions against the extreme deficit. Since the INFLP model handles the range of *PET* increments as interval numbers and tolerances the deficits with fuzzy sets, the results will show the influence of this increment.

Table 3 Simulated current inflows and future inflows under different climate change scenarios (unit: cm)

Month	1	2	3	4	5	6	7	8	9	10	11	12
Current	4.8	7.7	10.7	12.6	55.9	78.2	77.7	101.7	43.1	9.7	4.8	2.6
CCCM	4.1	8.1	7.4	14.0	63.6	109.2	78.2	122.0	60.8	9.9	4.3	2.0
Changes (%)	-16	5	-31	11	14	40	1	20	41	2	-12	-24
GFDL	5.1	7.6	11.0	11.7	60.8	74.9	72.8	135.1	48.7	14.7	3.7	2.8
Changes (%)	6	-1	2	-7	9	-4	-6	33	13	51	-23	8
GISS	5.5	5.5	11.2	16.9	51.9	120.6	103.3	127.7	57.1	9.7	5.5	2.5
Changes (%)	13	-21	5	34	-7	54	33	26	32	0	14	-3

Table 4 The change of monthly temperature under different climate change scenarios (unit: °C)

Month	1	2	3	4	5	6	7	8	9	10	11	12
Current	15.9	16.8	19.7	23.0	25.5	27.4	28.4	27.8	26.8	24.4	20.5	17.2
CCCM	18.6	20.5	24.5	27.2	29.7	29.9	30.5	29.5	29.4	26.8	22.9	20.7
Difference	2.7	3.7	4.7	4.2	4.2	2.5	2.1	1.8	2.6	2.5	2.4	3.4
GFDL	19.8	19.6	23.9	26.1	27.8	30.0	30.6	29.9	29.8	27.2	23.3	20.8
Difference	3.9	2.8	4.1	3.0	2.3	2.7	2.2	2.1	3.0	2.8	2.8	3.6
GISS	18.6	19.4	23.0	26.8	29.1	32.0	32.9	31.9	30.3	27.3	24.2	19.7
Difference	2.7	2.6	3.3	3.7	3.6	4.7	4.5	4.2	3.5	2.9	3.7	2.4

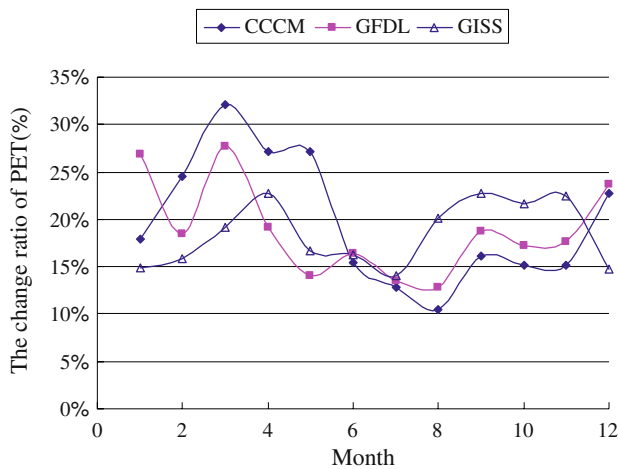


Fig. 4 The increment of PET under climate change

Table 5 The active storage and its corresponding membership function under different deficit cases (unit: 10^4 m^3)

	Tolerable deficits			
	5%	10%	15%	20%
K_a^{sup}	49,986	47,298	44,884	42,704
λ	0.0633	0.1136	0.1589	0.1977
K_a^{inf}	61,868	58,563	55,593	52,910
λ	0.1028	0.1508	0.1938	0.2327
$K_a^{\text{inf}} - K_a^{\text{sup}}$	11,882	11,265	10,709	10,206

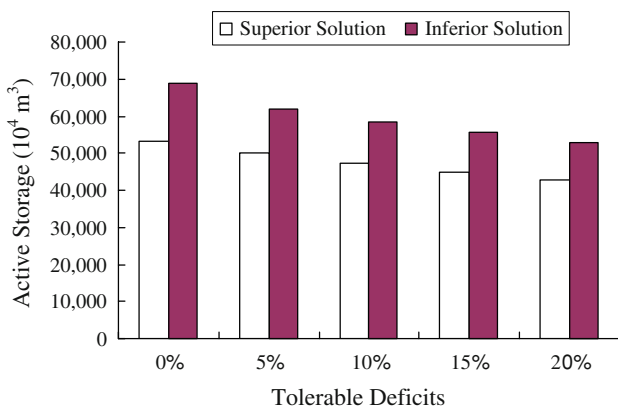


Fig. 5 Active storages under different deficit cases

Impacts on reservoir active storage

Sensitivity test for tolerable deficits with 5, 10, 15, and 20% shortages were performed in this study. The tolerable deficits can adjust the term of dy in M21 and M22 models. Optimal active storages for different levels of tolerable deficits are shown in Table 5 and Fig. 5. Other parameters were given in Tables 6 and 7. The active storages decrease

Table 6 The range of streamflows resulted from three GCM models under climate change

Month	Historical data(10^4 m^3)	$q_{t,y}^-$ (10^4 m^3)	$q_{t,y}^+$ (10^4 m^3)
1	2,072	1,974	2,448
2	2,908	2,372	3,170
3	3,861	2,930	4,113
4	4,448	4,252	58,81
5	18,035	16,728	20,394
6	25,240	24,059	37,822
7	25,499	23,900	33,874
8	33,143	40,223	43,936
9	14,625	16,603	20,555
10	3,879	40,11	5,589
11	2,136	1,892	2,499
12	1,415	1,302	1,562

with the increase of deficiency tolerance. The $K_{a,\text{min}}$ and $K_{a,\text{max}}$ are $53,363 \times 10^4$ and $68,960 \times 10^4 \text{ m}^3$ with no deficit, respectively. The estimated active storage is an interval number between $K_{a,\text{min}}$ and $K_{a,\text{max}}$, which is evaluated based on three GCMs predictions and can avoid possible bias due to using single GCMs prediction.

As the tolerable deficits increasing, active storages decrease and the difference between K_a^{sup} and K_a^{inf} decreased. It shows that the range of active storage will be decrease with tolerable deficits increasing. The difference between K_a^{sup} and K_a^{inf} is important information for decision makers, which uncertainty should be considered. The smaller the difference is, the easier the decision can be made. The difference between $K_{a,\text{min}}$ and $K_{a,\text{max}}$ is about $15,597 \times 10^4 \text{ m}^3$ without tolerable deficit. The difference becomes smaller when tolerable deficit becomes higher. Table 5 shows when the deficit is 5%, the difference between K_a^{sup} and K_a^{inf} is $11,882 \times 10^4 \text{ m}^3$ (24% reduction of the difference between $K_{a,\text{min}}$ and $K_{a,\text{max}}$). When the tolerable deficit is 20% the difference is $10,206 \times 10^4 \text{ m}^3$ (35% reduction of the difference between $K_{a,\text{min}}$ and $K_{a,\text{max}}$).

Conclusions

Uncertainties caused by the use of different GCMs' predictions may greatly affect the decision making of water resources management. The discrepancies among various GCMs' predictions cause difficulties to evaluate the impact study of climate change. Specially, the results from GCMs' are divergent in terms of quality and quantity. This research, including hydrological simulation and optimization model, provides a systematic framework to assess the reservoir capacity under climate change.

Table 7 The range of water demands resulted from WatBal model under climate change

Month	Historical demands (10^4 m^3)				Modified demands		
	Agricultural	Industrial	Domestic	Summary	$y_{i,y}^-$ (10^4 m^3)	$y_{i,y}^+$ (10^4 m^3)	
1	2,731	266	1,100	4,097	4,505	4,831	
2	11,488	240	1,100	12,828	14,641	15,650	
3	8,482	266	1,000	9,748	11,373	12,468	
4	10,584	249	1,000	11,833	13,858	14,706	
5	6,142	243	1,000	7,385	8,245	9,053	
6	8,321	193	1,000	9,514	10,797	10,879	
7	10,577	201	900	11,678	13,028	13,158	
8	7,979	202	800	8,981	9,817	10,582	
9	8,647	196	800	9,643	11,032	11,611	
10	7,949	202	1,100	9,251	10,453	10,975	
Changes of monthly weather data	11	3,287	192	1,100	4,579	5,075	5,318
Demands inflows	12	3,813	250	1,100	5,163	5,723	6,065

Hydrological simulation models were used to predict the impacts of climate change on streamflows and agricultural water demands. Streamflows were simulated by the use of WatBal model, while agricultural water demands were adjusted according to the changes of potential evapotranspiration. Different GCMs predict different temperature and precipitation fields under different climate conditions. With such predicted temperature and precipitation fields, diversified results of inflows and water demands may be obtained. Interval numbers were used in this study to describe the range of inflow and water demand variations resulting from different GCMs' predictions. Besides, the satisfaction of water supply was described by fuzzy relationships. Both interval numbers and fuzzy relationships were incorporated into a LP model to form an INFLP model. The optimized model determined the minimal and maximal required reservoir active storage.

By using several GCMs' predictions, the amount of information involved for consideration is increased. However, more uncertainties or variations are included for the determination process. The interval numbers have the property to account for the variation of inflows predicted by different models. The fuzzy membership functions can describe the real tolerance of deficit and present the satisfaction. By using the membership function of deficit, the range of active storage decrease. It is not only to test sensitivity of deficits, but also to reduce the interval of active storage. More important, membership function of deficit is feasible for real world applications. When fuzzy membership functions and interval numbers are used at the same time, the INFLP is built. The superior and inferior optimal solutions can be solved by the INFLP model, and a proper determination is made between these two extremes.

The result will be not affected easily by just using predictions from a single GCM model.

References

- Gleick PH (1987) The development and testing of a water balance model of climate impact assessment: modeling the Sacramento Basin. *Water Resour Res* 23(6):1049–1061
- Hamon WR (1961) Estimating potential evapotranspiration: proceedings of the American Society of Civil Engineers. *J Hydraul Div* 87(3):107–120
- Kaczmarek Z (1993) Water balance model of climate impacts analysis. *ACTC Geophys Pol* 41(4):1–16
- Kaczmarek Z, Krasuski D (1991) Sensitivity of water balance to climate change and variability. IIASA Working Paper, WP-91-047, Laxenburg, Austria
- Loucks DP, Stedinger JR, Douglas AH (1981) Water resource systems planning and analysis. Prentice-Hall, Inc., Englewood Cliffs
- McCabe GJ, Wolock DM, Hay LE, Ayers MA (1990) Effects of climatic change on the Thornthwaite moisture index. *Water Resour Bull* 26(4):633–643
- Negoita CV, Sularia M (1976) On fuzzy programming and tolerances in planning. *Econ Comp Econ Cybernet Stud Res* 1:3–15
- Shaocheng T (1994) Interval number and fuzzy number linear programming. *Fuzzy Sets Syst* 66:301–306
- Tung CP (2001) Climate change impacts on water resource of the Tsengwen Creek watershed in Taiwan. *J Am Water Resour Assoc* 37(1):167–176
- Tung CP, Haith DA (1995) Global warming effects on New York streamflows. *J Water Resour Plan Manag* 121(2):216–225
- Tung CP, Haith DA (1998) Climate change, irrigation, and crop response. *J Am Water Resour Assoc* 34(5):1071–1085
- Yates D (1996) WatBal: an integrated water balance model for climate impact assessment of river basin runoff. *Water Resour Dev* 12(2):121–139
- Zadeh LA (1965) Fuzzy sets. *Inf Control* 8:338–353