Assessment of Climate Change Impact on Water Balance of Forested and Farmed Catchments

Hoa X. Pham[1]; Asaad Y. Shamseldin[2]; and Bruce W. Melville[3]

Abstract: Water balance modeling is commonly used to quantify the impacts of climate change on water availability over a region or a catchment. Under climate change, significant variability in precipitation and evapotranspiration would dramatically affect the catchment water balance. Changes in soil and vegetation also have large impacts on water resources. However, current water balance modeling is mainly dependent on precipitation, while evapotranspiration is a fixed proportion of precipitation. Also, the interaction of the various phases of rainfall-runoff transformation within the soil is not fully computed. This paper for the first time investigates the combined effects of precipitation and evapotranspiration on the water balance of three typical forested and farmed catchments in the Waikato basin of New Zealand. A conceptual lumped water-soil model is employed to simulate the land phase of the hydrological cycle including soil moisture and ground water recharge from rainfall and evapotranspiration at catchment scale for both historical and future time slices. Observation data from 1971 to 2000 are used for model calibration. Future data up to year 2090 is obtained from a model. Future simulations are projected accordingly. The results show that changes in precipitation and especially potential evapotranspiration have a large impact on daily streamflow even though they do not much affect runoff volume. Streamflow is projected to dramatically decrease in 2030, 2060, and 2090 in the grassed catchments, while an inconsiderable reduction is found in the forested catchment. Even though bias correction is used to improve the accuracy of the potential evapotranspiration and the resulting catchment runoff, other errors are addressed but not yet resolved. They originate from regional climate model (RCM) outputs, scenarios, data observation, and interpretation as well as model performance. **DOI: 10.1061/(ASCE)HE.1943-5584.0001169.** *© 2015 American Society of Civil Engineers.*

Author keywords: Climate change; Water balance; Forested catchment; Farmed catchment; MIKE 11-NAM; Hadley Centre Coupled Model version 3 (HadCM3).

Introduction

Water balance models are commonly used for water resources assessment and management. This type of model acts as a valuable tool for assessing the hydrologic characteristics of diverse catchments and effective evaluation of the hydrologic consequences of climatic change (Xu and Singh 1998). They could also serve the purpose of quantifying climate change impacts on streamflow from precipitation, temperature, evapotranspiration, and soil moisture (Archer et al. 2010; Comnalicer et al. 2010; Esqueda et al. 2011; Ha 2009; Kim and Kaluarachchi 2009; Marks et al. 1993; Obeysekera et al. 2011; Vaitiekuniene 2005).

In the context of climate change, changes in precipitation exert direct and remarkable impacts on water resources (Archer et al. 2010; Esqueda et al. 2011; Kim and Kaluarachchi 2009; Pike et al., unpublished data, 2010). Similarly, water resources can be affected by changes in soil, vegetation, and evapotranspiration (Iturbe et al. 1999; Marks et al. 1993; Pike et al., unpublished data, 2010; D. Yates, "WatBal—An integrated water balance model for climate impact assessment of river basin runoff: International Institute for Applied Systems Analysis," working paper, Laxenburg, Austria). However, current water balance modeling is mainly dependent on precipitation, while evapotranspiration is treated as a function of temperature or precipitation (Novaky 2008; Jiang et al. 2007; Zhang et al. 2008). Moreover, these models do not fully take into account the interaction of the various phases of rainfall-runoff transformation within the soil, causing the inaccuracy of modeled water balance components of a catchment (Andrew and Dymond 2007; Jiang et al. 2007; Marks et al. 1993). Moreover, at the catchment scale, water balance modeling under different climate change scenarios is not fully studied (Ha 2009; Marks et al. 1993; Mauser and Bach 2009).

There are numerous methods to model the water balance of a catchment with regard to variation in time scale as well as the degree of model structure complexity. Being categorized by the model structure, the most commonly used models are lumped conceptual and distributed models. The distributed models partition precipitation into evapotranspiration and runoff, including the combined use of hydrological and atmospheric models (Mauser and Bach 2009). These models require a wide range of data, such as land cover, soil types, digital elevation model (DEM), and climate data. The most important input data are considered to be precipitation and evaporation (Xu and Singh 1998; Moreda 1999). These distributed models enable modeling runoff over large areas (Andrew and Dymond 2007) and thus require a lot of time and effort. The spatially lumped models are able to represent the land phase of the hydrological cycle including soil moisture and ground water recharge from rainfall, evapotranspiration for smaller areas, and simulated runoffs from overland flow, interflow, and base flow (Brauer 2007; Jiang et al. 2007; Vaitiekuniene 2005). Therefore, the lumped models can

[1]Ph.D. Candidate, Dept. of Civil and Environmental Engineering, Univ. of Auckland, Private Bag 92019, Auckland 1142, New Zealand (corresponding author). E-mail: xpha001@aucklanduni.ac.nz

[2]Associate Professor, Deputy Head (Research), Dept. of Civil and Environmental Engineering, Univ. of Auckland, Private Bag 92019, Auckland 1142, New Zealand.

[3]Professor, Dept. of Civil and Environmental Engineering, Univ. of Auckland, Private Bag 92019, Auckland 1142, New Zealand.

Note. This manuscript was submitted on April 16, 2014; approved on December 8, 2014; published online on January 23, 2015. Discussion period open until June 23, 2015; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Hydrologic Engineering***, © ASCE, ISSN 1084-0699/04015009(12)/$25.00.

link the soil matrix with the atmosphere, which importantly contributes to the hydrological system. At present, the lumped models are sufficient for rainfall-runoff simulation in combination with other routing models (Madsen et al. 2002). These advantages still remain when climate change impacts take place (Ha 2009).

Water balance models can also be categorized as daily, monthly, and annual models. They may have different requirements on input data, but give the likely outputs (Brauer 2007; Mauser and Bach 2009; White et al. 2011). The annual water balance model is not suitable in the context of climate change because this type of model only simulates annual streamflow volumes, while it is essential to determine the dynamic hydrological response of climatic change (Moreda 1999). In practice, monthly water balance models are commonly used because the main purposes are planning water resources and predicting the effects of climate change with their long-term variability. Additionally, monthly hydrometeorological data are most readily available (Xu and Singh 1998). These monthly models are particularly valuable for applications in which monthly, seasonal, and annual streamflow volumes are primary interests. Daily water balance models typically emphasize the dynamic aspects of hydrological processes (Wang et al. 2011). Therefore, they are reliable in assessing the impacts of climate change on the catchment water balance, especially for models with five or more parameters (D. Yates, "WatBal—An integrated water balance model for climate impact assessment of river basin runoff: International Institute for Applied Systems Analysis," working paper, Laxenburg, Austria).

To date, there are several studies dealing with the modeling of water balance under changing climate using the outputs of global circulation models (GCMs) and regional climate models (RCMs). Marks et al. (1993) used GCM data as input into a distributed hydrological model to simulate precipitation and potential evapotranspiration, which likely have large effects on water balance of the Columbia River basin in the United States. This is carried out for $1 \times CO_2$ and $2 \times CO_2$ scenarios. Inadequacy of this monthly gridded water balance model performance is caused by the topographical effect on precipitation, missing the snow component, and the effect of vegetation and water balance interaction. Kim and Kaluarachchi (2009) used a two-layer water balance model to simulate runoff of the Upper Blue Nile River basin from temperature and precipitation generated from six GCMs. In this paper, the correlation among stations and between temperature and precipitation were assumed to be constant with time. This is one of the major limitations of the study. A study in the Philippines by Comnalicer et al. (2010) used statistically downscaled GCM data to input into a monthly conceptual hydrological model, BROOK90, to simulate different water balance components of a forest watershed. Even though the results indicate a large amount of rainwater transferred to evaporation, the catchment water balance was modeled from a change in rainfall rather than in evaporation. One study in Germany by Brauer (2007) also investigated the effects of different catchment water balance components using the Wagenigen model and the Nedbør-Afstrømnings-Model (NAM), of which the latter outperforms the former with regards to summer discharge, peak discharge, and snow simulation. This was examined using observed data from 1971 to 2006. Vaitiekuniene (2005) applied the NAM to quantify water balance of a Lithuanian river basin. In this study, the rainfall-runoff model is assumed to be less sensitive to evaporation, but sensitive to rainfall. This is one of the major uncertainty sources of the model simulations based on observation over the period from 1993 to 2000.

Even though the daily lumped models are suited to assess the climate change impact and to predict streamflow, the data input requirement is a major disadvantage of these models. Data on precipitation, evapotranspiration, and soil over a long period is necessary but usually insufficient for both model calibration and prediction stages. This paper aims to model the catchment water balance from the combined effects of precipitation and evapotranspiration. Changes in precipitation and evapotranspiration are predicted using RCM Hadley Centre Coupled Model version 3 (HadCM3) outputs at a very fine spatial resolution, $0.05^0 \times 0.05^0$. Small forested and grassed catchments are selected as case studies. The change in catchment water balance from the past to the future times, 1961–2090, is investigated.

Study Regions and Data

Catchment Description

The Mangatawhiri, Mangaonua, and Whangamarino catchments located within the largest Waikato basin of New Zealand are selected as pilot case studies (Fig. 1). These small catchments are in the downstream of the Waikato River with similarities in size, elevation variation, and weather pattern, but they are different in terms of soil and vegetation characteristics. The drainage areas of the Mangatawhiri, Mangaonua, and Whangamarino catchments are approximately 104, 166, and 135 km^2, respectively. The most important land use in the Mangatawhiri catchment is forest, while grass is the dominant vegetation cover in the Whangamarino and the Mangaonua catchments.

The mean areal annual rainfall in these catchments varies between 1,200 and 1,600 mm. The mean annual evaporation varies between 800 and 1,100 mm. The mean annual streamflow recorded fluctuates from 540 to 760 m^3/s. The similar patterns in precipitation, evaporation, and flow in these catchments are shown in Figs. 2 and 3. The elevation of these catchments ranges between 40 and 300 m, stretching from upstream to downstream of the catchment.

Data

Data on daily precipitation and potential evapotranspiration (PET) are used as the key inputs to the daily water balance models. Daily observed precipitation, observed potential evapotranspiration (PET_{obs}), and observed discharge are obtained from gauging stations and used as a baseline representing the present climate. Data from at least one station located within the catchment or in the vicinity are used. This is due to the limitation of data observation (Fig. 1).

The mean areal precipitation and potential evapotranspiration generated from a regional climate model developed by the Hadley Centre in the United Kingdom (HadCM3) are used. An example of HadCM3 gridded temperature data is represented in Figs. S1–S3 for the selected catchments. These gridded data were tested in the previous studies by Pham et al. (2014a, b) to be reliable for studying the climate change. Data over two different periods, 1961 to 2000 and 2001 to 2090 are used to represent the present and future climates, respectively.

Future data from only one emissions scenario developed by the Intergovernmental Panel on Climate Change (IPCC) in the Special Report on Emissions Scenarios (SRES), A2 scenario, is then used for all simulations. This A2 emissions scenario is selected because it was one of the marker scenarios developed through the IPCC (2000, 2007). Furthermore, the A2 scenario is a common one used by the National Institute of Water and Atmospheric Research (NIWA) to study the climate change effects and impacts assessment for New Zealand local governments (Ministry for the Environment 2008).

The summary of data selected for the study is presented in Table 1.

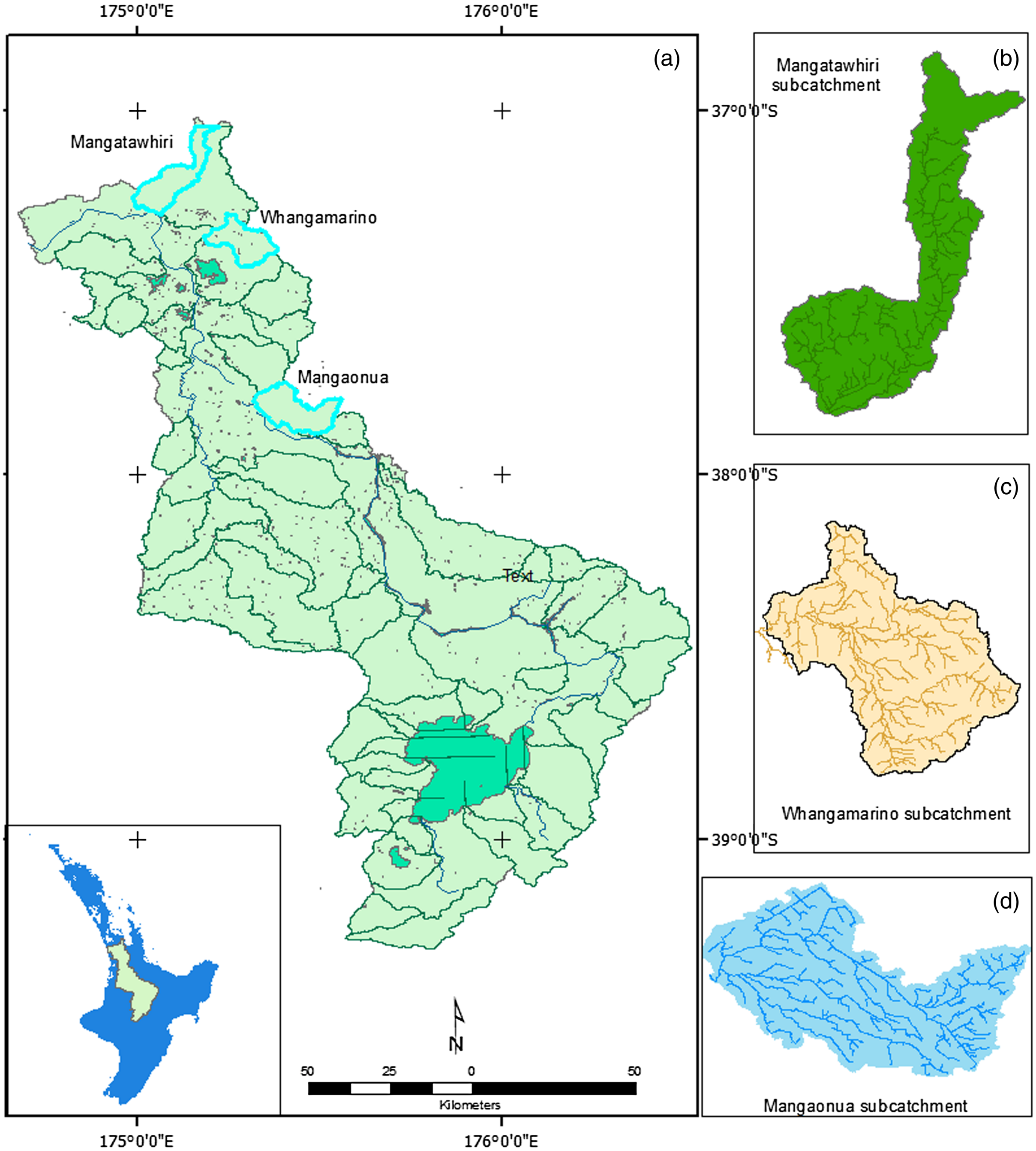

Fig. 1. Location of selected catchments: (a) Waikato basin of New Zealand; (b) Mangatawhiri subcatchment; (c) Whangamarino subcatchment; (d) Mangaonua subcatchment

Materials and Methods

This section presents the information on data analysis and the daily water balance model as well as its performance to simulate and predict the water balance for both historical and future climates. As a result, the change in water balance in three catchments with different characteristics is investigated.

Bias-Corrected Potential Evapotranspiration

In previous studies, Pham et al. (2014a, b) examined the adaptability of daily precipitation and daily PET for the Waikato catchment, which were generated from RCM HadCM3 outputs. The daily precipitation was directly extracted from the HadCM3 model, while the PET was computed from different climatic variables (i.e., temperature, relative humidity, radiation, and wind speed), which were also extracted from the same HadCM3 model. The PET was estimated using the ET_0Cal program, which is based on the FAO-56 method developed by the Food and Agriculture Organization (Raes 2012). The RCM-generated precipitation was evaluated against the observation during the 1961–2000 period. The RCM-generated PET was compared with the observed potential evapotranspiration (PET_{obs}) over the same period. In this paper, the PET_{obs} was computed from raised pan evaporation at station location using the Tait-Woods empirical formula. In New Zealand, this formula is preferred in computing potential

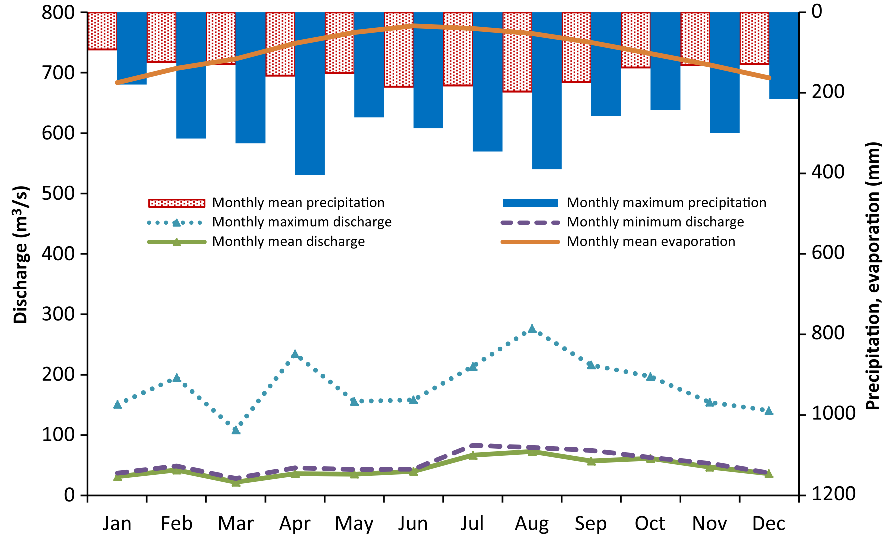

Fig. 2. Graphs of monthly precipitation, evaporation, and discharge at station in the Mangatawhiri catchment

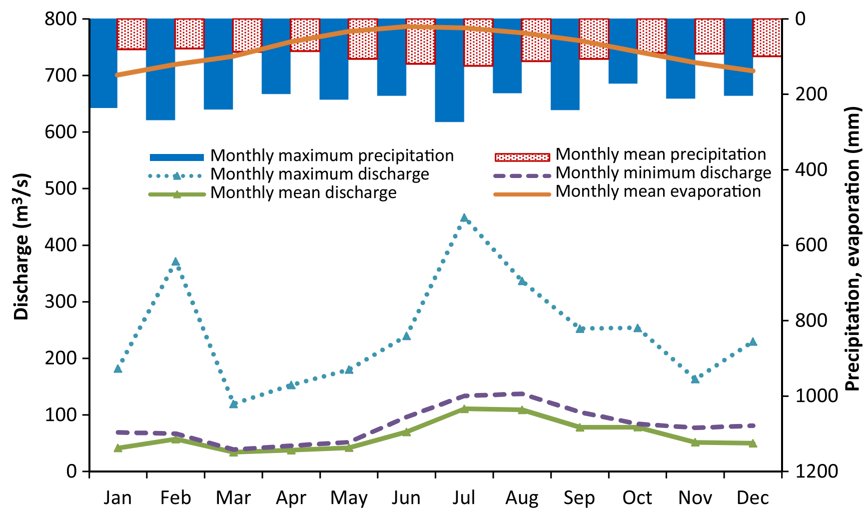

Fig. 3. Graphs of monthly precipitation, evaporation, and discharge at stations in the Mangaonua catchment

Table 1. Summary on Historical Data Used in the Study

Number	Catchment	Gridded precipitation	Gridded PET	Observed precipitation	Raised pan evaporation	Observed discharge
1	Mangatawhiri	1961–2090	1961–2090	1973–1983	1973–1983	1971–2000
2	Whangamarino	1961–2090	1961–2090	1982–1990	1982–1990	N/A
3	Mangaonua	1961–2090	1961–2090	1981–1996	1981–1996	1981–2000

evapotranspiration from pan evaporation (Tait and Woods 2007). The results reveal that the daily precipitation time series generated from the HadCM3 model is suitable for future prediction using a frequency analysis of partial duration series of daily precipitation, while the PET series computed from HadCM3 variables ($\mathrm{PET_{RCM}}$) is underestimated in winter months and overestimated in summer months when it is compared with $\mathrm{PET_{obs}}$. Therefore, the bias-correction method is employed to correct $\mathrm{PET_{RCM}}$ in this study in order to give more accurate runoff production and streamflow.

The bias-correction method is expressed mathematically as follows (Habte 2013):

$$\mathrm{PET_{bias-corrected}}(i) = \mathrm{PET_{RCM}}(i) \cdot \frac{\overline{\mathrm{PET_{obs}}}}{\overline{\mathrm{PET_{RCM}}}} \qquad (1)$$

where $\mathrm{PET_{bias-corrected}}(i)$ = corrected RCM potential evapotranspiration on day i (mm); $\mathrm{PET_{RCM}}(i)$ = raw RCM precipitation on day i (mm); $\overline{\mathrm{PET_{obs}}}$ = mean monthly potential evapotranspiration from observation for a given month (mm); and $\overline{\mathrm{PET_{RCM}}}$ = mean monthly potential evapotranspiration from RCM HadCM3 variables for a given month (mm).

In this paper, the mean areal PET from RCM is corrected to the observation at stations that are located within the catchment or in vicinity.

Lumped and Conceptual Model

This paper employs a lumped conceptual rainfall-runoff model, namely, NAM, for simulating the precipitation-evapotranspiration-runoff process over three selected catchments. This model was originally developed by the Department of Hydrodynamics and Water Resources at the Technical University of Denmark. This model enables satisfactorily accounting for the spatial and temporal variability of hydrologic processes, especially when the catchment size is small [Danish Hydraulic Institute (DHI) 2009]. In this case, the catchment is considered as homogenous in terms of hydrometeogeology, which could give the best simulation of catchment water balance. As widely used, the NAM is applicable for a number of catchments with different hydrological regimes and climatic conditions (DHI 2009; Brauer 2007; Hafezparast et al. 2013; Nayaka et al. 2013; Vaitiekuniene 2005).

Basically, the NAM model represents various components of the rainfall-runoff transformation process by continuously accounting for the water content in four different and mutually interrelated storages. Each of those represents different physical elements of the catchment (DHI 2009). This model can be applied for individual catchment, although regional uniformity does not exist, and then is able to transpose to ungauged catchment (Vaitiekuniene 2005). In addition, the NAM allows users to take artificial interventions in the hydrological cycle such as irrigation and groundwater abstraction into account. However, the NAM also exhibits some errors in simulated runoff, which is too much dependent on human interference, likely reservoir operation (Brauer 2007).

The model consequently simulates river flow from overland flow, interflow, and base flow as a function of the water storage in the four storages. The basic input requirements for the NAM consist of model parameters, initial conditions < meteorological data including precipitation and potential evapotranspiration, and runoff data for model calibration and validation.

Model Calibration and Validation

Due to the discontinuity of observed data series, the calibration and validation periods for two catchments are different. Table 2 gives more details on selected events for model calibration and validation stages. A trial-and-error procedure is applied to determine the optimized model parameter sets, which give the most reliable results for both calibration and validation processes. The most physically sensitive parameters to the catchment characteristics are presented in Table 3.

Model Performance Evaluation

In order to assess the reliability of model used in this study, different statistical coefficients are used consisting of the coefficient of efficiency (CE) developed by Nash and Sutcliffe (1970) and the Kling-Gupta efficiency coefficient (KGE) developed by Gupta et al. (2009). These coefficients are commonly used to test the agreement between observation and simulation. Similar to CE, KGE is also sensitive to time to peak. However, the application of KGE has advantages over the CE criteria. In particular, the use of CE underestimates the variability and mean of flows but introduces the largest errors in peak runoff. In contrast, the KGE presents variability, mean of flow, and linear correlation well (Pechlivandis et al. 2010). Also, root-mean-square error (RMSE) and water balance error (WBL) coefficients are used. The four coefficients are expressed as follows, which are used for both calibration and validation stages:

$$CE = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{2}$$

$$KGE = 1 - ED \tag{3}$$

with

$$\alpha = \frac{\sigma_{S_i}}{\sigma_{O_i}}; \qquad \beta = \frac{\bar{S}}{\bar{O}}; \qquad r = \frac{\sum_{i=1}^{n}[(O_i - \bar{O})(S_i - \bar{S})]}{\sqrt{(O_i - \bar{O})^2}\sqrt{(S_i - \bar{S})^2}} \tag{4}$$

where r = linear conversion coefficient and

$$ED = \sqrt{(r-1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}} \tag{6}$$

$$WBL = \frac{\sum_{i=1}^{n}(S_i - O_i)}{n} \tag{7}$$

Table 2. Model Calibration and Validation Periods for Different Catchments

Number	Catchment (gauge identifier)	Calibration	Validation
1	Mangatawhiri (459.11)	January 1, 1973, to December 31, 1981	January 1, 1982, to December 31, 1983
2	Mangaonua (421.1)	January 1, 1981, to December 31, 1993	January 1, 1994, to December 31, 1996

Note: Model calibration and validation is not applied for the ungauged Whangamarino catchment.

Table 3. Summary on NAM Parameters from Madsen et al. (2002)

Number	Parameter	Unit	Description	Range
1	U_{max}	mm	Upper zone storage capacity	1–100
2	L_{max}	mm	Lower zone storage capacity	20–500
3	CQOF	—	Overland flow runoff coefficient	0–1
4	TOF, TIF, TG	—	Overland flow, interflow, and recharge threshold coefficients, respectively	0–0.95
5	$CK_{1,2}$	h	Time constant for overland flow and interflow routing	3–48
6	CK_{IF}	h	Time constant for interflow from the surface storage	500–1,000
7	CK_{BF}	h	Base flow time constant for base flow from the groundwater storage	500–5,000

where O_i = observed stream flow on day $i(\mathrm{m}^3/\mathrm{s})$; S_i = simulated stream flow on day $i(\mathrm{m}^3/\mathrm{s})$; $\bar{O}$ = mean of the observed stream flow data; and $\bar{S}$ = mean of the simulated stream flow data.

Modeling of Future Runoff Production and Assessment of Catchment Water Balance

After getting the optimum sets of the NAM parameters, they are then used to predict future runoff from future precipitation and potential evapotranspiration data. A 30-year-based time series is generated for this purpose.

The parameter sets optimized for the Mangaonua catchment are adapted to simulate streamflow in the Whangamarino catchment because no data on discharge are available in the Whangamarino catchment. In fact, these two catchments are similar, having the same size, elevation variation, soil, and vegetation types.

For the comprehensive assessment of future projections, the decadal 30-year that is the standard normal period defined by the World Meteorological Organization (WMO) is used. Future catchment runoff volume is predicted from future precipitation and PET data for the 2001–2030, 2031–2060, and 2061-2090 periods, which are in this paper defined as future subscenarios A2a, A2b, and A2c, respectively. The change in runoff volume is assessed among future scenarios and against observation periods between year 1973 and 1996 depending on catchments.

Results and Discussions

MIKE-NAM Calibration and Validation

The optimized parameter sets for two Mangatawhiri and Mangaonua catchments are presented in Table 4. Inspection of the table shows that the most significant difference is found for $U_{\max}$ and corresponding $L_{\max}$, $\mathrm{CK}_{1,2}$, TOF, TIF, and TG parameter values. These are known as the most sensitive parameters to the catchment characteristics. Especially, these parameters are strongly related to soil permeability and surface interception capacity, which directly influence the streamflow generation from groundwater and interflow within the soil profile (DHI 2009; Sun and Liu 2010).

Further examination of Table 4 reveals that the values of $U_{\max}$, $L_{\max}$, $\mathrm{CK}_{1,2}$, TOF, TIF, and TG computed for the Mangaonua catchment are higher than those of the Mangatawhiri catchment. This suggests a resistance of permeable soil and grassed surface, which requires a long time to generate ground flows and interflows in the Mangaonua catchment. In contrast, a porous soil texture in the forested Mangatawhiri catchment requires less time but high threshold values allowing rain water to infiltrate and travel through soil layers to river. This result is consistent with the main properties of recent soils.

Table 5 presents information about model performance evaluation using five different coefficients, which are explained in the previous section. In general, the model performs well for the Mangaonua catchment with higher values of CE and KGE and lower values of RMSE and WBL in comparison with its performance for the Mangatawhiri catchment. A relatively poor agreement between observation and simulation is found in the Mangatawhiri catchment. This may be due to the fact that the water balance input data consisting of the selected precipitation and evaporation do not fully represent the catchment conditions (Boughton 2005). In particular, the precipitation and the evaporation data in the Mangaonua catchment are obtained from the stations located within the catchment, while the corresponding data used for the Mangatawhiri catchment runoff modeling are from one station in the catchment and one station in the vicinity. The station location can be seen in Figs. 2 and 3.

Also, Figs. 4–11 introduce the visualization of model calibration and validation on a daily basis for the Mangatawhiri and Mangaonua catchments. However, for the overall testing consisting of both calibration and validation periods, the model performance is likely to be acceptable with the value of WBL of 0%, which suggests a perfect simulation in terms of the runoff volume accuracy.

The Whangamarino catchment with dominant ultic, gley, and recent soil types, which have low permeability, may constrain the flow generation. This characteristic is relatively similar to the dominant soil type in the Mangaonua catchment. Moreover, these two catchments are dominantly covered with grasses. Therefore, the adapted NAM parameter of the Mangaonua catchment is considered to be valid for the Whangamarino catchment. Further examination of Table 5 also shows that the model performs well for the Whangamarino catchment. The value of WBL is 5.9%. A comparison is made between simulated runoff in the Whangamarino catchment and observed runoff in the Mangaonua catchment.

Table 4. NAM Parameters for Different Catchments

Parameter	Unit	Lower bound	Upper bound	Final value: Mangatawhiri (forested)	Final value: Mangaonua (grass)
$U_{\max}$	mm	5	35	**6**	**20**
$L_{\max}$	mm	50	350	**70**	**201**
CQOF	—	0	1	0.45	0.35
CKIF	—	500	1,000	762	773
$\mathrm{CK}_{1,2}$	—	3	35	**14.14**	**26.68**
TOF	—	0	0.7	**0.44**	**0.395**
TIF	h	0	1	**0.293**	**0.909**
TG	h	0	0.7	**0.058**	**0.482**
CKBF	h	500	4,000	2,698	2,981

Note: Parameters' values in bold indicate that they are the most sensitive ones.

Projected Changes in Future Water Balance

The validated parameter sets for each catchment are used to project the future streamflow for the SRES A2 scenario. The 30-year

Table 5. Model Evaluation for Different Catchments

Catchment	Calibration RMSE	Calibration CE	Calibration KGE	Calibration WBL (%)	Validation RMSE	Validation CE	Validation KGE	Validation WBL (%)	Simulation WBL (%)
Mangatawhiri	3.98	0.42	0.48	3.0	7.80	0.40	0.49	35.40	0.0
Mangaonua	1.31	0.59	0.72	4.1	2.15	0.55	0.66	0.7	0.0
Whangamarino	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	5.9

Note: NAM parameters for the Whangamarino catchment are adapted from Mangaonua-NAM parameters; Whangamarino simulated discharge and volume are compared with the Mangaonua observation.

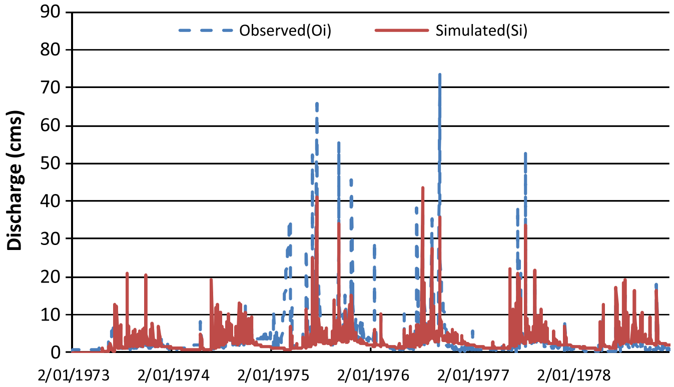

Fig. 4. Calibrated hydrograph for Mangatawhiri catchment during the 1973–1978 period

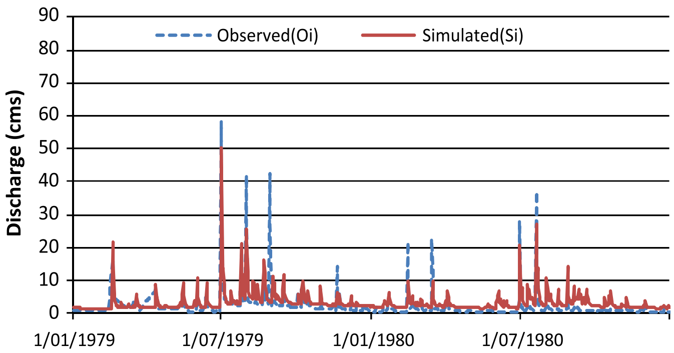

Fig. 5. Validated hydrograph for Mangatawhiri catchment during the 1979–1980 period

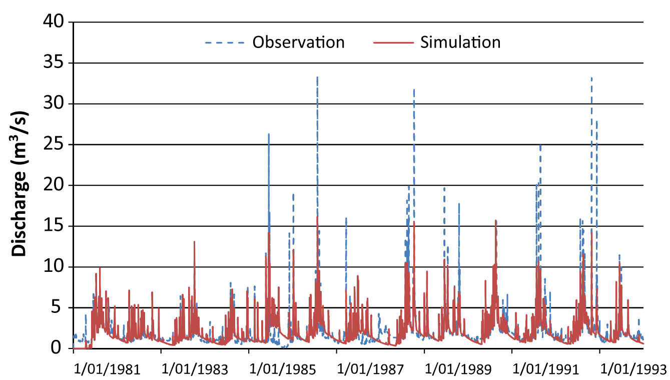

Fig. 6. Calibrated hydrograph for Mangaonua catchment during the 1981–1993 period

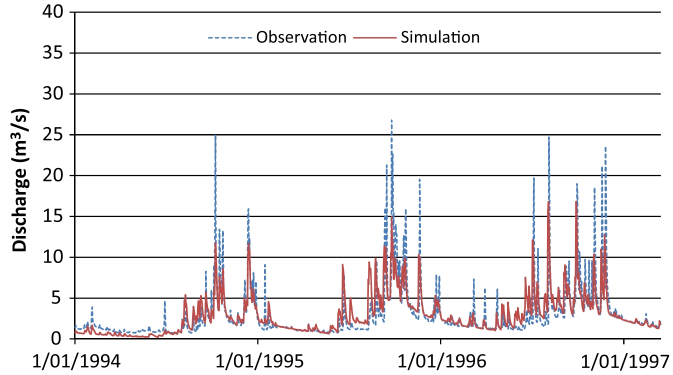

Fig. 7. Validated hydrograph for Mangaonua catchment during the 1994–1996 period

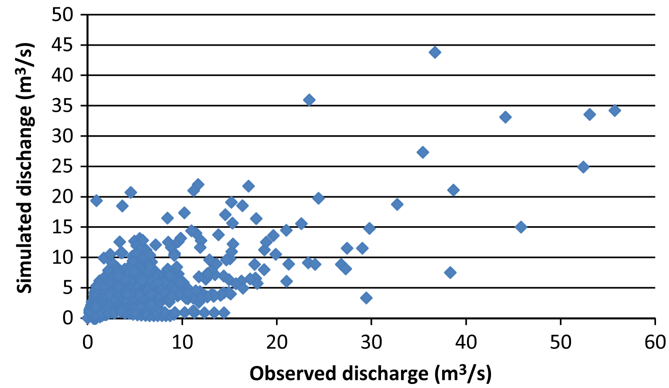

Fig. 8. Model calibration: Observed versus simulated daily discharge of at Station 459.11 in the Mangatawhiri catchment

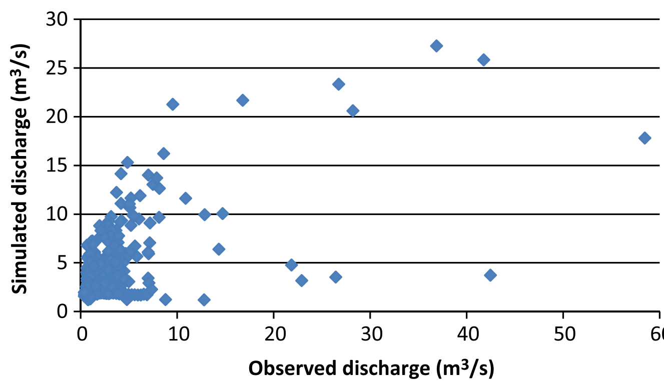

Fig. 9. Model validation: Observed versus simulated daily discharge of at Station 459.11 in the Mangatawhiri catchment

time flow series are projected for subscenarios A2a, A2b, and A2c in accordance with the 2001–2030, 2031–2060, and 2061–2090 periods. A comparison between future projections of streamflow computed from un-bias-corrected PET and bias-corrected PET is made accordingly.

Table 6 presents information on the projected daily runoff and its variation. In all three catchments, the mean daily runoff is projected to increase for the A2a and A2b scenarios, then to slightly decrease for the A2c scenario. The mean daily runoff varies from 1.4 to 2.06 m^3/s. However, the variability of projected daily runoff is relatively high with a coefficient of variation (COV) value that fluctuates around 1.0. This differs from catchment to catchment with the highest variability degree found in the Mangatawhiri catchment. The Whangamarino and Mangaonua catchments experience a less variability in runoff projections.

Figs. 12–14 show the changes in runoff volume among future subscenarios. In general, a decrease in runoff volume is found with time. Particularly, water yields in the A2b scenario are less than those of the A2a scenario, but higher than those of the A2c scenario. However, the degree of change is different from catchment to catchment. Examination of these figures reveals that the

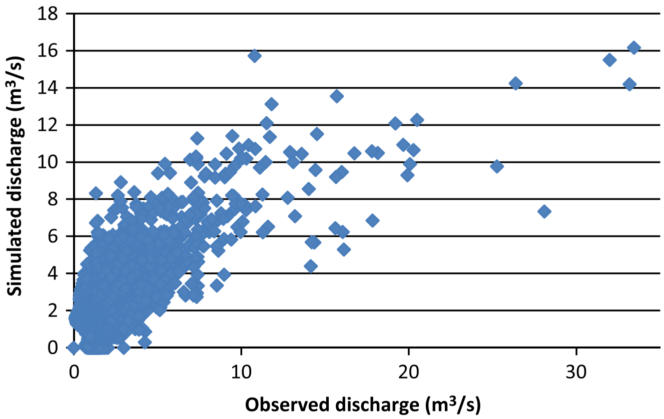

Fig. 10. Model calibration: Observed versus simulated daily discharge at Station 421.4 in the Mangaonua catchment

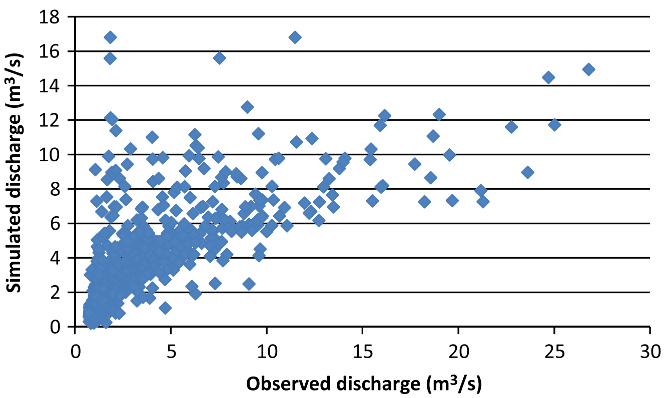

Fig. 11. Model validation: Observed versus simulated daily discharge at Station 421.4 in the Mangaonua catchment

Table 6. Future Projections of Daily Runoff for Different Catchments

		Un-bias corrected		Bias corrected	
Catchment	Scenarios	Mean	COV	Mean	COV
Mangatawhiri	A2a	2.00	1.04	3.04	0.60
	A2b	2.02	1.03	3.10	0.61
	A2c	1.91	1.28	3.23	0.60
Whangamarino	A2a	1.80	1.00	3.10	0.60
	A2b	1.64	1.06	3.18	0.61
	A2c	1.40	1.22	3.31	0.60
Mangaonua	A2a	2.06	0.95	2.46	0.63
	A2b	1.91	1.01	2.50	0.65
	A2c	1.70	1.09	2.60	0.65

Note: Scenarios are defined as A2a for the 2001–2030 period, A2b (2031–2060), and A2c (2061–2090).

most dramatic reduction in runoff volume occurs in both grassed catchments, Whangamarino and Mangaonua. For the Mangaonua catchment as an example, runoff volume is projected to be approximately 1,900, 1,750, and 1,550 m^3 for the years 2030, 2060, and 2090, respectively. However, the projected runoff volume for the forested Mangatawhiri catchment is 1,900, 1,850, and 1,800 m^3 for the years 2030, 2060, and 2090, respectively. The overall change in runoff volume also can be seen in Table 7.

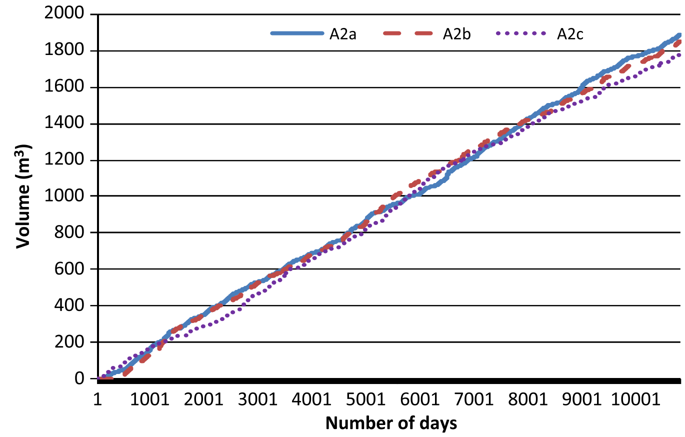

Fig. 12. Runoff volumes for the Mangatawhiri catchment for the periods 2001–2030, 2031–2060, and 2061–2090 corresponding to Scenarios A2a, A2b, and A2c

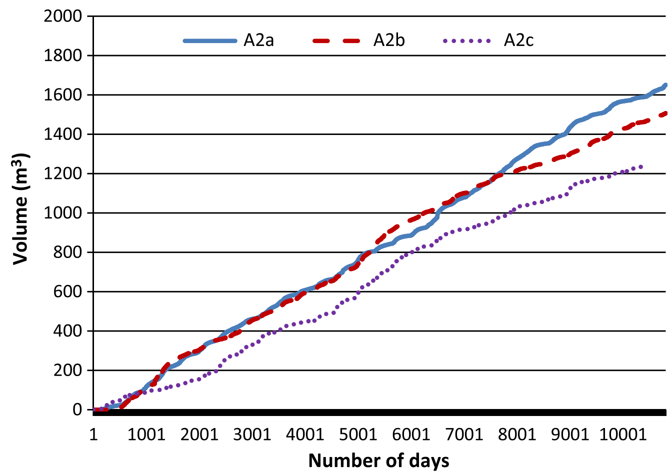

Fig. 13. Runoff volumes for the Whangamarino catchment for the periods 2001–2030, 2031–2060, and 2061–2090 corresponding to Scenarios A2a, A2b, and A2c

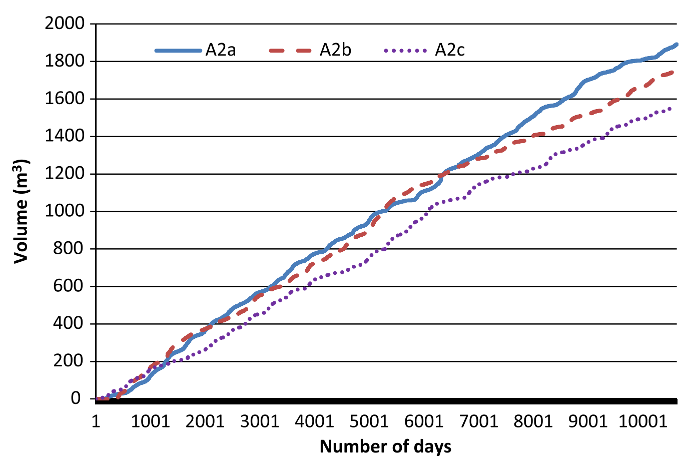

Fig. 14. Runoff volumes for the Mangaonua catchment for the periods 2001–2030, 2031–2060, and 2061–2090 corresponding to Scenarios A2a, A2b, and A2c

Table 7. Future Projections of Catchment Water Balance

Catchment	Future projection (change in runoff volume) (%)		
	2001–2030 (A2a)	2031–2060 (A2b)	2061–2090 (A2c)
Mangatawhiri	−33.0	+6.2	−15.0
Whangamarino	−6.0	−3.0	−15.0
Mangaonua	+3.3	−8.0	−8.0

Note: Change in runoff volume for the A2a scenario corresponds to the observed volume, and that for the A2b and A2c scenarios are compared to the change in runoff volume for the A2a scenario; plus and minus signs indicate an increase and decrease in runoff volume, respectively.

This decreasing trend in water volume is consistent with increasing PET and decreasing precipitation that occurs in the study catchments (Pham et al. 2014a, b). This tendency remains when runoff volume is computed from bias-corrected PET. An adjustment is made between individual months. PET rate is added up approximately 1.0 to 1.2 times during the summer months (November to March), while it is reduced by approximately 0.7 to 0.8 times in the winter months. As a consequence, the bias-corrected daily runoff dramatically increases compared with no bias correction (Table 6). However, the monthly flow experiences a significant change in volume from catchment to catchment as shown in Figs. 15–17.

Further examination of Table 6 reveals that the bias-corrected mean daily runoff increases from scenario to scenario, and rises much higher over the un-bias-corrected runoff. The value of bias-corrected runoff ranges between 2.5 and 3.31 m^3/s, equivalent to 1.3 to 2.7% higher than the projected runoff with un-bias correction. However, the variation in bias-corrected runoff is much less than the un-bias-corrected one with the value of COV approximately 0.6.

As can also be seen from the Figs. 15–17, the correction of daily RCM-generated PET to the observed evaporation at the station has a dramatic effect on the catchment runoff. Overall, the reduction of PET in the winter months raises the mean daily runoff in the same months up to 25%. The same rate is also found in the decrease of mean daily runoff in the summer months when the PET increases by 1.0 to 1.2 times. The distribution of corrected runoff seems to be more reliable than that of the uncorrected one because it suits the local weather, which has more evaporation but less precipitation in the summer and vice versa in the winter. Therefore, the use of the bias-correction method is necessary to model monthly and seasonal runoffs in the study catchments.

Combined or Integrated Errors in Modeling Future Streamflow

This section presents major errors that may be affecting the accuracy of streamflow simulations and projections. This paper utilizes various data sources as well as employing different models and programs. Moreover, in order to simplify and make use of certain techniques applied with scarce data availability, some assumptions

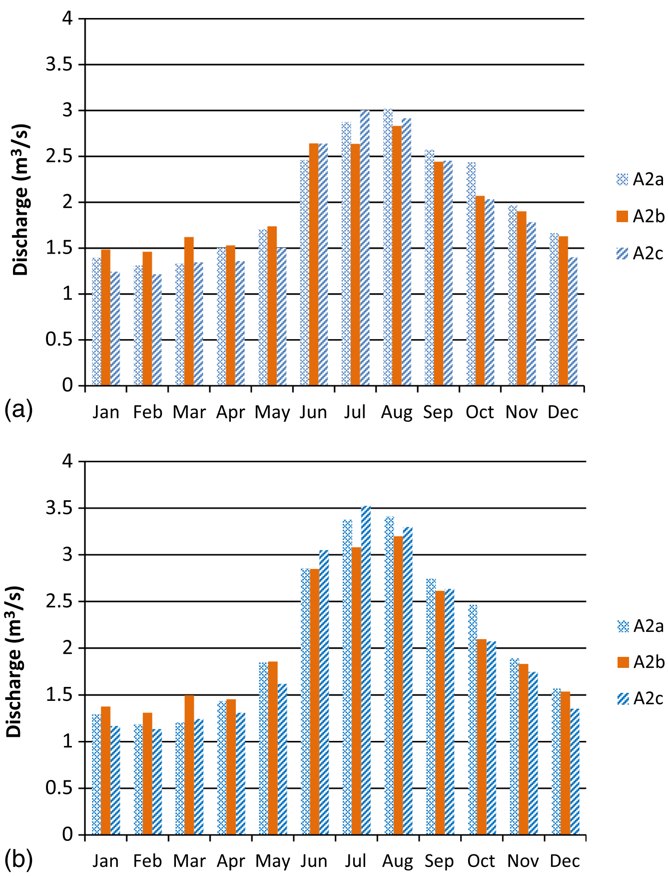

Fig. 15. River flow computed from (a) un-bias-corrected PET; (b) bias-corrected PET the Mangatawhiri catchment for Scenarios A2a, A2b, and A2c

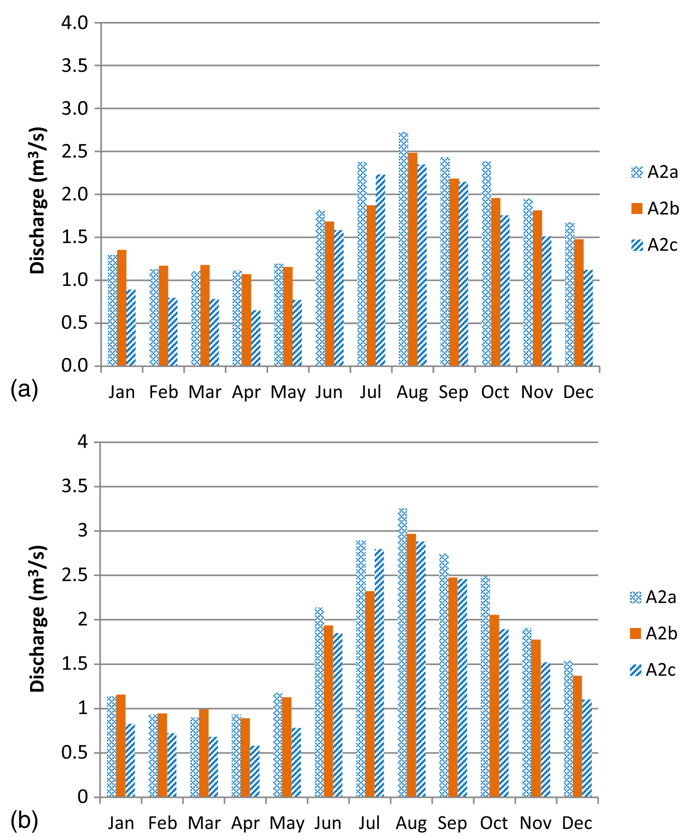

Fig. 16. River flow computed from (a) un-bias-corrected PET; (b) bias-corrected PET the Whangamarino catchment for Scenarios A2a, A2b, and A2c

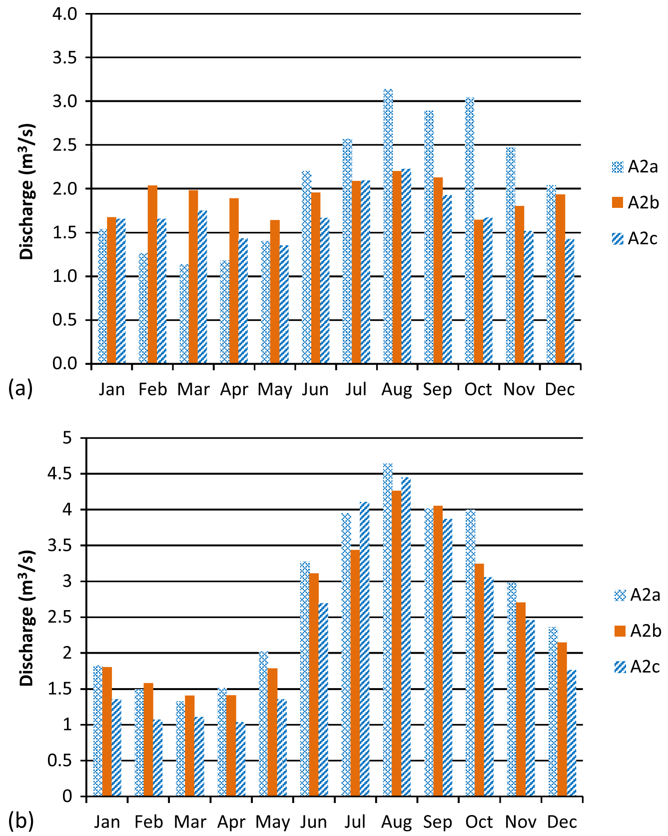

Fig. 17. River flow computed from (a) un-bias-corrected PET; (b) bias-corrected PET the Mangaonua catchment for Scenarios A2a, A2b, and A2c

are also made in this paper. These errors persistent in the modelling of catchment water balance may originate from the following sources.

Uncertainty Embedded in Regional Climate Model

Literature has indicated that both technical and scientific limitations are tolerant in any GCMs and RCMs. These limitations include parameterization, resolutions, initial and boundary conditions, intermodel variability, and validation and verification issues (Foley 2010; Pielke 2012; Rummukainen 2010). Many errors in the GCMs stem from the RCMs because "the dynamics and physics of the RCM are the same as in the GCM except for certain parameterization constants that had to be set differently to account for the higher resolution of the RCM" (Drost et al. 2007). Also, initial and boundary conditions are used differently to model a nested region (Randall et al. 2007). In this case, the structure of these RCMs becomes more complex, resulting in intermodel variability (Chen et al. 2012; Dubrovsky 2009; Mpelasoka 2000; Mujumdar and Ghosh 2008). As a result, RCM-generated variables are biased and not all of them are bias corrected with the observed data during the validation and verification processes (Pelt et al. 2009; Sunyer et al. 2012; Drost et al. 2007).

Uncertainty Adds from Future Scenarios

The IPCC SRES scenarios are used as the standard dealing with the study on the impact of future changes, which is developed based on historically decadal trends in climate and human activities (Bakker et al. 2011; Esqueda et al. 2011; IPCC 2000). All regional climate change scenarios are driven by the GCM scenarios that are rather limited for climate and hydrological extremes (Bronsterst et al. 2007; Qian et al. 2010; Wang et al. 2012). This is a major consequence of scenario uncertainty on the climate change signal (Baguis et al. 2010). Similar to the driving GCM scenarios, high-resolution RCM scenarios developed from regional climate model experiments also have inherent uncertainty during modeling (Mearns et al. 2003; Schmidli et al. 2007).

Uncertainty Caused by Observation and Usage

For the study catchments, observation network and data are limited or discontinuous. The use of observed data from nearby stations happens because climate variables between target and study stations are correlated. However, the surrounding environments of the selected stations are not exactly the same. In fact, the measured climate variables are strongly dependent on local environment (Craig 2006; Roderick and Graham 2002).

Uncertainty Created by Hydrological Models and Other Programs

This paper uses various programs and models ranging from input data extraction and correction to hydrological simulation. For the data extraction programs, gridded data are extracted from RCM output by the latitude and longitude of position on the surface of the study catchments. The accuracy of extracted data for that catchment may be ± 1 grid cell when the catchment boundary lies within two or more gird cells. This error may be minor for a catchment with large area, but it could become to be major for small catchments. In fact, the size of each grid cell of HadCM3 output used is 5×5 km. The area of study catchments varies from 104 to 166 km^2, covering approximately 5 to 10 grid cells at 5-km resolution. The ET_0Cal program is used to compute PET from climate variables and it is based on some certain assumptions of local climate. This can create errors in the resulting PET. For the hydrological NAM, it is important to relate model parameters with catchment properties that directly drive the streamflow generation as well as runoff production. Furthermore, simulation of runoff in the ungauged catchments is constrained because the correlation between the calibrated parameters and catchment characteristics is not accounted for in the current models (Boughton 2006; Boughton and Chiew 2007). However, as demonstrated in many studies, the modeled results are strongly dependent on the input data rather than the effects of the characteristics of a catchment and its hydrological responses (Boughton 2004, 2005, 2006; Droogers and Allen 2002).

Uncertainty Caused by Study Assumptions

Due to the existing circumstance of study catchments and their data, this PAPER has made some assumptions as follows:

- Model parameters are adapted for a ungauged catchment;
- Model parameters are unchanged under climate change;
- Only one IPCC SRES A2 scenario is considered; and
- Data on precipitation and evapotranspiration computed from RCM over the 1961–2000 period are used as historically observed precipitation during the model calibration stage.

These typical underlying assumptions may affect the accuracy of modeled results. In particular, errors persistent in model parameters could still stem from a gauged catchment to an ungauged catchment. For example, the defaulted criteria of NAM performance evaluation could cause a subjective bias in which only absolute values of observation and predictions are used to compute the water balance error coefficient. Furthermore, the valid model parameters may not be adequate for a future projection in which climate change takes place. This is another error in modeling future runoffs. In addition, the use of only one SRES A2 scenario may not provide a comprehensive assessment of catchment response to climate change. In this regard, more SRES scenarios could give a better assessment. Finally, the data over the 1961–2000 period may not fully present the climate state of the past century. This could result in a difficulty in investigating the change in catchment runoffs from the past to the future.

Conclusions and Recommendations

This paper investigates the impacts of climate change on the catchment water balance components. The results show that the variability of daily precipitation and the potential evapotranspiration are likely to have large impacts on catchment streamflow. This puts more emphasis on the combined effects of daily precipitation and evapotranspiration on streamflow.

A simulation of historical streamflow from observed precipitation and evaporation is considered to be in good agreement with the observed flow. The values of KGE range between 0.5 and 0.7 for the Mangatawhiri and Mangaonua catchments, respectively. In fact, only a few observation stations located within the catchments and in their vicinity are used due to the sparse observation network and limited data. Moreover, this study aims to examine the change in streamflow from present to future times, hence any systematic errors tolerated in the historical simulations may not have significant impacts on the future projections. The validated model parameters, therefore, are accepted for future projections of streamflow of those catchments as well as of ungagged catchments.

Owing to the evaluation of NAM performance, the results also reveal that the model performance can much improve if the observed data on precipitation and evaporation are representative of those catchments. This also means that more streamflow and more runoff volume are expected to be produced from precipitation. For the three catchments used in this paper, the selected precipitation stations are located downstream or even near the catchment outlet where the elevation is just about one-third or one-fourth of what is in the upstream of the catchment.

By comparing the patterns of monthly streamflow conducted from un-bias-corrected and bias-corrected evapotranspiration, the results also demonstrate that if the evapotranspiration rate increases or decreases by 1.0 times, the mean daily streamflow consequently decreases or increase by the same rate at 25%.

However, this study utilizes various data sources and programs that may incur different errors. Hence, the accuracy of the results may be affected. For the catchments with limited observed data, the improvement of regional climate model outputs is essential. Likewise, the data extraction programs and hydrological models need more improvements to be validated in more different regions, which still remain a challenge for scientists as well as program developers.

Supplemental Data

Figs. S1–S3 are available online in the ASCE Library (www.ascelibrary.org).

References

Andrew, R. M., and Dymond, J. R. (2007). "A distributed model of water balance in the Motueka catchment, New Zealand." *Environ. Modell. Softw.*, 22(10), 1519–1528.

Archer, D. R., Forsythe, N., Fowler, H. J., and Shah, S. M. (2010). "Sustainability of water resources management in the Indus basin under changing climatic and socio economic conditions." *Hydrol. Earth Syst. Sci.*, 7(2), 1883–1912.

Baguis, P., Roulin, E., Willems, P., and Ntegeka, V. (2010). "Climate change scenarios for precipitation and potential evapotranspiration over central Belgium." *Theor. Appl. Clim.*, 99(3–4), 273–286.

Bakker, A. M. R., Hurk, B. J. J. M. V., Bessembinder, J. J. E., and Kroon, T. (2011). "Standard years for large-scale hydrological scenario simulations." *Environ. Modell. Softw.*, 26(6), 797–803.

Boughton, W. (2004). "The Australian water balance model." *Environ. Modell. Softw.*, 19(10), 943–956.

Boughton, W. (2005). "Catchment water balance modelling in Australia 1960–2004." *Agric. Water Manage.*, 71(2), 91–116.

Boughton, W. (2006). "Calibrations of a daily rainfall-runoff model with poor quality data." *Environ. Modell. Softw.*, 21(8), 1114–1128.

Boughton, W., and Chiew, F. (2007). "Estimating runoff in ungauged catchments from rainfall, PET and the AWBM model." *Environ. Modell. Softw.*, 22(4), 476–487.

Brauer, C. (2007). *The Issel catchment: Water balance study and rainfall-runoff modeling*, Wageningen Univ., Germany.

Bronsterst, A., Kolokotronis, V., Schwandt, D., and Straub, H. (2007). "Comparison and evaluation of regional climate scenarios for hydrological impact analysis: General scheme and application example." *Int. J. Climatol.*, 27, 1579–1594.

Chen, H., Xu, C. Y., and Guo, S. (2012). "Comparison and evaluation of multiple GCMs, statistical downscaling and hydrological models in the study of climate change impacts on runoff." *J. Hydrol.*, 434–435, 36–45.

Comnalicer, E. A., Criz, R. V. O., Lee, S., and Im, S. (2010). "Assessing climate change impacts on water balance in the Mount Makiling forest, Philipines." *J. Earth Syst. Sci.*, 119(3), 265–283.

Craig, I. P. (2006). "Comparison of precise water depth measurements on agricultural storages with open-water evaporation estimates." *Agric. Water Manage.*, 85(1–2), 193–200.

DHI (Danish Hydraulic Institute). (2009). "MIKE 11: A modelling system for rivers and channels." Copenhagen, Denmark.

Droogers, P., and Allen, R. G. (2002). "Estimating reference evapotranspiration under inaccurate data conditions." *Irrig. Drain. Syst.*, 16(1), 33–45.

Drost, F., Renwick, J., Bhaskaran, B., Oliver, H., and McGregor, J. (2007). "Simulation of New Zealand's climate using a high-resolution nested regional climate model." *Int. J. Climatol.*, 27(9), 1153–1169.

Dubrovsky, M. (2009). "Uncertainties in multi-model climate projections." *9th EMS Annual Meeting, 9th European Conf. on Applications of Meteorology (ECAM)*, ⟨http://meetings.copernicus.org/ems2009/⟩.

Esqueda, G. S. T., Norena, J. E. O., Garcia, C. G., and Conde, C. (2011). "Vulnerability of water resources to climate change scenarios. Impacts on the irrigation districts in the Guayalejo-Tamesí river basin, Tamaulipas, México." *Atmosfera*, 24(1), 141–155.

Foley, A. M. (2010). "Uncertainty in regional climate modelling: A review." *Prog. Phys. Geog.*, 34(5), 647–670.

Gupta, H. V., Kling, H., Yilmaz, K., and Martinez, G. (2009). "Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling." *J. Hydrol.*, 377(1–2), 80–91.

Ha, N. T. T. (2009). "Water resources management in Ba River basin under future development and climate change scenarios." Asian Institute of Technology, Bangkok, Thailand.

Habte, G. L. (2013). "Remote sensing and regionalization for integrated water resources modelling in upper and middle Awash River basin, Ethiopia." Univ. of Twente, Enschde, Netherlands.

Hafezparast, M., Araghinejad, S., Fatemi, S. E., and Bressers, H. (2013). "A conceptual rainfall-runoff model using the auto calibrated NAM models in the Sarisoo River." *Hydrol. Current Res.*, 4(1), 2–6.

IPCC (Intergovermental Panel on Climate Change). (2000). "Emission scenarios: A special report of IPCC Working Group III." Geneva.

IPCC (Intergovermental Panel on Climate Change). (2007). "Climate change 2007: Synthesis report: Contribution of Working Groups I, II and III to the fourth assessment report of the Intergovernmental Panel on Climate Change." Geneva.

Iturbe, I. R., Porporato, A., Ridolfi, L., Isham, V. S., and Coxi, D. R. (1999). "Probabilistic modelling of water balance at a point: The role of climate, soil and vegetation." *Proc. Royal Soc.*, 455(1990), 3789–3805.

Jiang, T., Chen, Y. D., Xu, C. Y., Chen, X., Chen, X., and Singh, V. P. (2007). "Comparison of hydrological impacts of climate change simulated by six hydrological models in the Dongjiang basin, south China." *J. Hydrol.*, 336(3–4), 316–333.

Kim, U., and Kaluarachchi, J. J. (2009). "Climate change impacts on water resources in the upper Blue Nile river basin, Ethiopia." *J. Am. Water Resour. Assoc.*, 45(61361–1378).

Madsen, H., Wilsona, G. T., and Ammentorp, H. C. (2002). "Comparison of different automated strategies for calibration of rainfall-runoff models." *J. Hydrol.*, 261(1–4), 48–59.

Marks, D., King, G. A., and Dolph, J. (1993). "Implications of climate change for the water balance of the Columbia river basin, USA." *Clim. Res.*, 2, 203–213.

Mauser, W., and Bach, H. (2009). "PROMET—Large scale distributed hydrological modelling to study the impact of climate change on the water flows of mountain watersheds." *J. Hydrol.*, 376(3–4), 362–377.

Mearns, L. O., Giorgi, F., Whetton, P., Pabon, D., Hulme, M., and Lal, M. (2003). "Guidelines for use of climate scenarios developed from regional climate model experiments." *DDC of TPCC TGCIA Rep.*, ⟨http://www.ipcc-data.org/⟩.

Ministry for the Environment. (2008). "Climate change effects and impacts assessment: A guidance manual for local government in New Zealand." Wellington, New Zealand.

Moreda, F. (1999). "Conceptual rainfall-runoff models for different time steps with special consideration for semi-arid and arid catchments." Vrije Universiteit Brussel, Brussels, Belgium.

Mpelasoka, F. S. (2000). "GCM-derived climate change scenarios and their impacts on New Zealand water resources." Massey Univ., Palmerston North, New Zealand.

Mujumdar, P. P., and Ghosh, S. (2008). "Modeling GCM and scenario uncertainty using a possibilistic approach: Application to the Mahanadi River, India." *Water Resour. Res.*, 44(6), 1–15.

Nash, J. E. and Sutcliffe, J. V. (1970). "River flow forecasting through conceptual models. Part I—A discussion of principles." *J. Hydrol.*, 10(3), 282–290.

Nayaka, P. C., Venkatesh, B., Krishna, B., and Jain, S. K. (2013). "Rainfall-runoff modeling using conceptual, data driven, and wavelet based computing approach." *J. Hydrol.*, 493, 57–67.

Novaky, B. (2008). "Climate change impact on water balance of Lake Balaton." *Water Sci. Technol.*, 58(9), 1856–1870.

Obeysekera, J., Irizarry, M., Park, J. S., Barnes, J., and Dessalegne, T. (2011). "Climate change and its implications for water resources management in south Florida." *Stoch. Environ. Res. Risk Assess.*, 25(4), 495–516.

Pechlivandis, I. G., Jacksona, B., and McMillanb, H. (2010). "The use of entropy as a model diagnostic in rainfall-runoff modelling." *Int. Environmental Modelling and Software Society (iEMSs), 5th Biennial Meeting*, D. A. Swayne, W. Yang, A. A. Voinov, A. Rizzoli, and T. Filatova, eds., Ottawa.

Pelt, S. C. V., Kabat, P., Ter Maat, H. W., Vanden Hurk, B. J. J. M., and Weerts, A. H. (2009). "Discharge simulations performed with a hydrological model using bias corrected regional climate model input." *Hydrol. EarthSyst. Sci.*, 13(12), 2387–2397.

Pham, H., Shamseldin, A., and Melville, B. (2014a). "Downscaling of daily precipitation and projection of future extreme precipitation." *J. Hydrol. Eng.*, 19(4), 807–815.

Pham, H., Shamseldin, A., and Melville, B. (2014b). "Future projection of potential evapotranspiration over forested and grassed catchments." *19th Congress of the Asia and Pacific Div. of the Int. Association for Hydro-Environment Engineering and Research (IAHR-ADP)*, Hanoi, Vietnam.

Pielke, R. A. (2012). "Regional climate downscaling: What's the point?" *Eos*, 93(5), 52–53.

Qian, B., Gameda, S., Jong, R., Falloon, P., and Gornall, J. (2010). "Comparing scenarios of Canadian daily climate extremes derived using a weather generator." *Clim. Res.*, 41(2), 131–149.

Raes, D. (2012). "ET0 calculator—Reference manual." Food and Agriculture Organization of the United Nations (FAO), Rome, Italy.

Randall, D. A., et al. (2007). "Contribution of working Group I to the fourth assessment report of the intergovernmental panel on climate change." *Climate models and their evaluation*, S. Solomon, et al., eds., Cambridge University Press, Cambridge, U.K.

Roderick, M. L., and Graham, D. F. (2002). "The cause of decreased pan evaporation over the past 50 years." *Science*, 298(5597), 1410–1411.

Rummukainen, M. (2010). "State-of-the-art with regional climate models." *Adv. Rev. WIREs Clim. Change*, 1(1), 82–96.

Schmidli, J., et al. (2007). "Statistical and dynamical downscaling of precipitation: An evaluation and comparison of scenarios for the European Alps." *J. Geophys. Res.*, 112(D4), 1–20.

Sun, F., and Liu, Y. (2010). "Sensitivity analysis and automatic calibration of a rainfall-runoff model using multi-objectives." *Knowledge-Based and Intelligent Information and Engineering Systems—14th Int. Conf., KES 2010, Proc.*, Vol. 6276, 90–99.

Sunyer, M. A., Madsen, H., and Ang, P. H. (2012). "A comparison of different regional climate models and statistical downscaling methods for extreme rainfall estimation under climate change." *Atmos. Res.*, 103, 119–128.

Tait, A., and Woods, R. (2007). "Spatial interpolation of daily potential evapotranspiration for New Zealand using a spline model." *J. Hydrometeorol.*, 8(3), 430–438.

Vaitiekuniene, J. (2005). "Application of rainfall-runoff model to set up the water balance for Lithuanian river basins." *Environ. Res. Eng. Manage.*, 1(31), 34–44.

Wang, Q. J., Pagano, T. C., Zhou, S. L., Hapuarachchi, H. A. P., Zhang, L., and Robertson, D. E. (2011). "Monthly versus daily water balance models in simulating monthly runoff." *J. Hydrol.*, 404, 166–175.

Wang, X., Yang, T., Shao, Q., Acharya, K., Wang, W., and Yu, Z. (2012). "Statistical downscaling of extremes of precipitation and temperature and construction of their future scenarios in an elevated and cold zone." *Stoch. Environ. Res. Risk Assess.*, 26(3), 405–418.

White, E. D., et al. (2011). "Development and application of a physically based landscape water balance in the SWAT model." *Hydrol. Processes*, 25(6), 915–925.

Xu, C. Y., and Singh, P. (1998). "A review on monthly water balance models for water resources investigations." *Water Resour. Manage.*, 12(1), 20–50.

Zhang, L., Potter, N., Hickel, K., Zhang, Y., and Shao, Q. (2008). "Water balance modeling over variable time scales based on the Budyko framework—Model development and testing." *J. Hydrol.*, 360(1–4), 117–131.