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Assessment of climate change impacts on water balance components of Heeia watershed in Hawaii

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ABSTRACT

Study region: Heeia watershed, Oahu, Hawaii, USA.
Study focus: Hydrological models are useful tools for assessing the impact of climate change in watersheds. We evaluated the applicability of the Soil and Water Assessment Tool (SWAT) model in a case study of Heeia, Pacific-island watershed that has highly permeable volcanic soils and suffers from hydrological data scarcity. Applicability of the model was enhanced with several modifications to reflect unique watershed characteristics. The calibrated model was then used to assess the impact of rainfall, temperature, and CO_2 concentration changes on the water balance of the watershed.
New hydrological insights for the study region: Compared to continental watersheds, the Heeia watershed showed high rainfall initial abstraction due to high initial infiltration capacity of the soils. The simulated and observed streamflows generally showed a good agreement and satisfactory model performance demonstrating the applicability of SWAT for small island watersheds with large topographic, precipitation, and land-use gradients. The study also demonstrates methods to resolve data scarcity issues. Predicted climate change scenarios showed that the decrease in rainfall during wet season and marginal increase in dry season are the main factors for the overall decrease in water balance components. Specifically, the groundwater flow component may consistently decrease by as much as 15% due to predicted rainfall and temperature changes by 2100, which may have serious implications on groundwater availability in the watershed.

1. Introduction

Island communities, including those of the Hawaiian Islands, rely on local water resources, which may be very sensitive to climate change (Pulwarty et al., 2010). Yet, future prediction of the state of water resources at a scale of a typical island watershed is hampered by the small geographical area of the island, which is not resolved in climate models, and by the scarcity of hydrological data that are needed to capture variability within such a watershed. While the integrated assessment of hydrology and climate has been getting increased attention in the field of hydrology and related disciplines (Wilby et al., 2006), there are very few studies on expected changes in water budgets in small island watersheds (Safeeq and Fares, 2012).

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Evidence of climate change in Hawaii includes historical observations of temperatures and sea- level data, which show increasing trend as a result of warming climate (Firing et al., 2004; Giambelluca et al., 2008; Diaz et al., 2011). Globally, researchers have reported that extreme climate change may cause frequent incidents of flooding and drought, shortage of water supply, landslides, soil erosion, and damage to existing infrastructures (Beniston et al., 2007). Some of these problems have already been documented in Hawaii. For example, baseflow and streamflow of Hawaiian streams have showed a decreasing trend due to a combined effect of increasing groundwater withdrawals and lower precipitation (Oki, 2004; Bassiouni and Oki, 2013).

Recent studies on climate change have shown that rainfall over the Hawaiian Islands is expected to decrease during the nominal wet season (November to April) but marginally increase during the dry season (May to October) (Timm and Diaz, 2009; Timm et al., 2011). Given that approximately 70% of the annual rainfall happens during the wet season, Hawaii is expected to face an overall reduction in annual rainfall leading to a decline in sustainability of groundwater recharge (Burnett and Wada, 2014). In addition, Diaz et al. (2011) and Giambelluca et al. (2008) reported that air temperature in the Hawaiian Islands is anticipated to increase in the future. Such an increase will influence components of the hydrologic cycle as it drives evapotranspiration. Other factors negatively influencing water resources include population growth (http://uhero.prognoz.com/TableR.aspx) and water demand increase (Engott et al., 2015). With such expected problems, climate change simulations and analysis of its anticipated impacts on hydrological processes are invaluable tools in the design and planning of mitigation measures to address the adverse consequences of climate change.

The general procedure for assessing the impacts of climate change on water resources and watershed processes is first to project plausible future climate change scenarios through the use of Global Climate Models (GCMs). Recently, different GCMs of the Coupled Model Intercomparison Project Phase 5 (CMIP5) have been developed for future climate change projections, which are based on Representative Concentration Pathways (RCPs) of greenhouse gases by 2100 (IPCC, 2014). The GCMs determine the effects of changing concentrations of greenhouse gases on global climate variables, such as temperature, rainfall, evapotranspiration, humidity, and wind speed. However, the direct use of GCMs' outputs for local scale hydrologic analysis can result in inadequate model outputs, due to their coarse spatial and temporal resolutions (Elsner et al., 2010). Therefore, the results of the GCMs should be downscaled to either regional or local scale through the use of statistical or dynamical downscaling techniques (Salathe et al., 2007; Timm and Diaz, 2009). In the following step, spatially semi-distributed, physically-based hydrological models, such as the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998), can be used to examine and assess the impacts of climate change (Bae et al., 2011). Due to its wide utility and applicability, different versions of SWAT have been used for several studies throughout the world (Krysanova and Arnold, 2008; Gassman et al., 2014). SWAT has been used for hydrological modeling (Ndomba et al., 2008a,b; Thampi et al., 2010; Notter et al., 2012; Strauch et al., 2012; Kumar et al., 2014; Abbaspour et al., 2015; Leta et al., 2015; Nyeko, 2015; Yen et al., 2016), soil erosion and sediment transport modeling (Ndomba et al., 2008a,b; Betrie et al., 2011), climate change impact studies on streamflow (Githui et al., 2009; Mango et al., 2011), and land use change and management practices impact assessment on streamflow and sediment yield (Betrie et al., 2011; Mango et al., 2011). In addition, SWAT has been internationally used for tile-drain, nutrients transport, and pesticide modeling with (out) model modifications, especially in lowland agricultural watersheds (Koch et al., 2013; Moriasi et al., 2013; Bannwarth et al., 2014; Fohrer et al., 2014; Bauwe et al., 2016; Cho et al., 2016; Golmohammadi et al., 2016). The previous studies confirm the successful use of SWAT across a broad range of watershed scales, environmental problems, hydrologic and pollutant conditions.

While previous studies on watershed hydrologic modeling focused on continental watersheds, there is a need to test the applicability of SWAT for pacific island watersheds that are characterized by relatively small-scale, steep topography, large precipitation gradients, volcanic rock outcrops, and scarcity of data. These characteristics are typical for the Hawaiian watersheds and there are only a few applications of other hydrological models (Sahoo et al., 2006; Apple, 2008; Safeeq and Fares, 2012), which were mainly focused on the dryer, leeward side of the island of Oahu, Hawaii. An exception is Apple (2008) who evaluated the applicability of Hydrologic Simulation Program-Fortran (HSPF) for Kaneohe watershed, which is located in the wet, windward section of the island. She concluded that the HSPF model produced acceptable results for annual and monthly streamflow simulations, but daily streamflow predictions were not accurate. Thus, a need exists for watershed model development in the windward, wet side of the islands that will be very sensitive to climate change, as an essential task for an integrated water resources management, climate change impact assessment, and adaptive strategy to climate change.

The specific objective of this study was to illustrate that a watershed model can be applied for water balance analysis in highly permeable (volcanic soils) watershed with challenging characteristics not yet captured or addressed in existing studies and that a model can be applied for water balance analysis in future climate change scenarios. This study addressed this objective in two steps:

a) evaluate the applicability and suitability of the SWAT model for streamflow simulations in Heeia under scarcity of hydrological data;
b) assess the impact of three different climate variables (rainfall, temperature, and CO_2 concentration) change on the water balance components in the watershed.

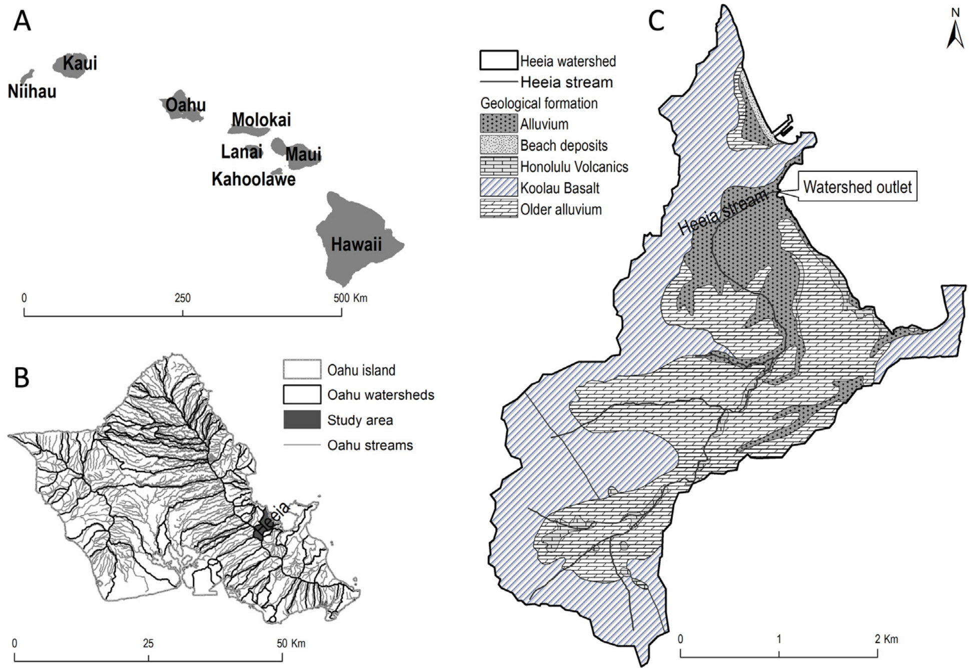

Fig. 1. Location of the Heeia watershed on Oahu Island (B), and geological formations of Heeia watershed (C).

2. Material and methods

2.1. Soil and Water Assessment Tool (SWAT) model

SWAT is a watershed-scale, physically-based, semi-distributed hydrologic model that operates on different time steps (Arnold et al., 1998). A watershed is divided into a number of sub-basins that have homogeneous climatic conditions (Van Liew et al., 2005). Sub-basins are further sub-divided into hydrological response units (HRUs) based on a homogenous combination of land use, soil type, and slope value (Arnold et al., 2011). The SWAT model has been widely applied for worldwide research dealing with hydrologic assessment, soil erosion/sediment transport, water quality analyses, climate and land use changes, and watershed management impact studies (Gassman et al., 2007).

SWAT uses a water balance equation that includes precipitation, surface runoff, actual evapotranspiration, lateral flow, percolation, baseflow, and deep groundwater losses components (Neitsch et al., 2011). The model applies a modification of the Soil Conservation Service Curve Number (SCS-CN) method (USDA-SCS, 1986), which determines the surface runoff based on the area's hydrologic group, land use, and antecedent moisture content for each HRU.

In this study, the SCS-CN method for surface runoff simulations, the Penman-Monteith method for potential evapotranspiration estimation, and the variable storage routing method for daily streamflow routing were used. Penman-Monteith method was selected due to its suitability for Hawaiian climatic conditions (Giambelluca et al., 2014). In addition, from the three PET options offered by SWAT, this is the only method modified to account for the effects of CO_2 concentration on leaf stomatal conductance and evapotranspiration (Neitsch et al., 2011), which is important for climate change studies.

2.2. The study area

The Heeia watershed is located in the north-east, windward part of Oahu Island, Hawaii (Fig. 1, panel B). Main water uses are related to public water supply, aquaculture, and cultural land-use practices (KBAC, 2007). In Hawaii, interaction among trade winds, topography, thermal effects, and trade wind inversion provide the most varied rainfall patterns in the world. The wet season (November to April) rainfall events are intensive, frequent, and generally produced by cooler trade winds but often interrupted with mid-latitude frontal and southwest wind (Kona storms) systems (Chu and Chen, 2005). The dry season (May to October) rainfall events are low, less frequent, and mainly formed by warmer trade winds that constantly uplifts cumulus clouds towards the Islands from the ocean (Chu and Chen, 2005). The Heeia watershed covers an area of 11.5 km^2 and receives annual average rainfall of 1800 mm. However, due to persistent trade winds and orographic lifting of moist air, the watershed experiences rainfall spatial variability over short distances, whereby regions of maximum rainfall are located at the mountains (Giambelluca et al., 2013). Consequently, the annual average rainfall of the watershed varies from 1205 to 3020 mm and increases with elevation at a rate of 4.5 mm m^{-1} (Giambelluca et al., 2013). This information was

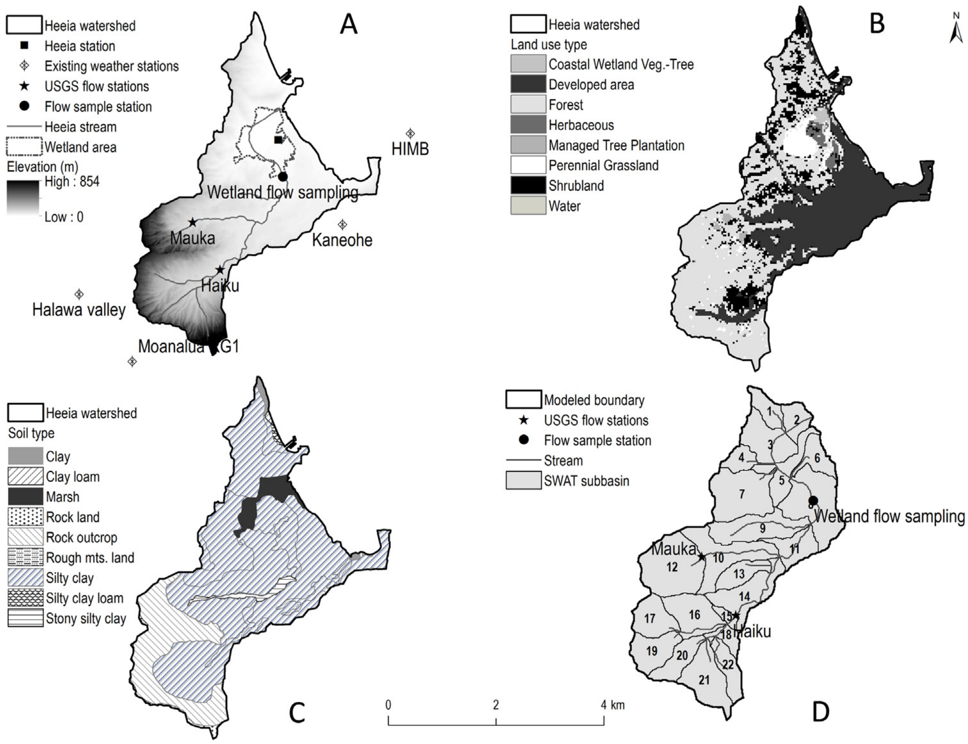

Fig. 2. The Heeia Digital Elevation Model with hydro-meteorological stations (A), land use (B), soil type (C), and delineated sub-basins with corresponding flow gauging locations (D). Mauka station was not used in this study because it did not have available data for the investigated period.

used to capture rainfall variability in the watershed hydrologic model. Elevation in the watershed ranges from 0 to 854 m above mean sea level, with an average slope of 40%.

The geological formations of the watershed are dominated by Koolau basalt (46%), followed by older alluvium (37%) (Sherrod et al., 2007). The Koolau basalt, which is characterized by very high hydraulic conductivity of up to 1500 m d^{-1} (Lau and Mink, 2006), largely covers the mountain region of the watershed (Fig. 1, panel C). The latter may have significant effects on the hydrological processes (e.g., groundwater recharge), with the Koolau ridge of the watershed receiving the highest recharge. The land use in the watershed is dominated by forest (47%), followed by developed areas (27%), and shrub land (14%), whereas the remaining areas are covered by other land uses (grassland, dry coastal strand, herbaceous vegetation and water bodies) (Fig. 2, panel B). The watershed has 15 different soil types that were classified on the basis of the location names as well as hydraulic conductivity, water holding capacity, slope, and soil depth, such as Alaeloa, Hanalei, Kaneohe, Lolekaa, Waikane silty clay soils. The model used this detail information, however, to simplify the display in Fig. 2, both the original land use and soil data were grouped into major categories. The watershed top-soil layer is mainly covered by volcanic silty clay soils that accounts for 76% of the watershed (Fig. 2, panel C). The rock outcrop, rock land, and rough mountainous terrains that mainly occur at the crest and upstream part of the watershed, constitute 19%, while the other soils (marsh, clay, silty clay loam, and clay loam) only account for 5% of the watershed (Fig. 2, panel C).

2.3. Data

The ArcGIS compatible SWAT 2012 was built up based on the following data:

- A 10 × 10 m Digital Elevation Model (DEM) obtained from the Department of Commerce (DOC), National Oceanic and Atmospheric Administration (NOAA), Center for Coastal Monitoring and Assessment (CCMA);
- 1:24,000 scale soil maps from Soil Survey Geographic (SSURGO) database provided by the U.S. Department of Agriculture, Natural Resources Conservation Service (USDA-NRCS);
- A 30 × 30 m land use map of the Landfire land cover of Hawaii, Wildland Fire Science, Earth Resources Observation, and Science Center of the U.S. Geological Survey (USGS).

Daily rainfall data was obtained for the period of 2000 to 2013 from the Hawaii Institute of Marine Biology (HIMB) at Coconut Island (Dr. Kuulei Rodgers, personal communication, 2014). Rainfall data were also available from the USGS stations at North Halawa Valley, the Halawa Tunnel and at Moanalua rain gauge number 1 (http://waterdata.usgs.gov/nwis/sw), and from the National Climatic Data Center (NCDC) of NOAA at Kanoehe station (http://www.ncdc.noaa.gov/cdo-web/datasets)

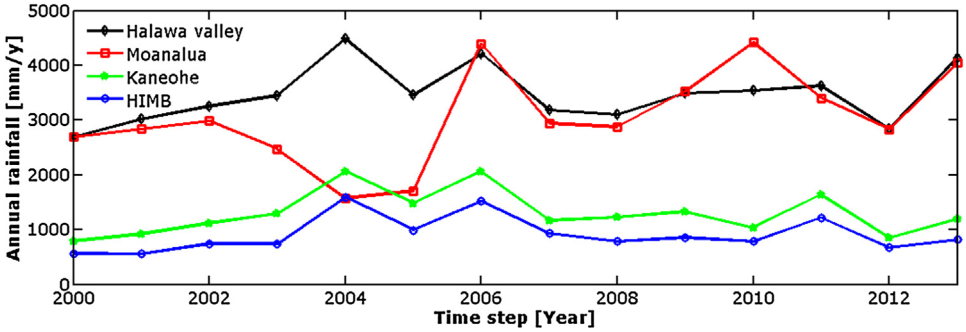

Fig. 3. Annual average rainfall data of stations in the vicinity of the Heeia watershed used in this study.

Table 1
The correlation coefficient values of daily rainfall data among the used stations. Bold signifies strong correlation.

Source	Stations	Correlation			
		Halawa valley	Moanalua RG1	Kaneohe	HIMB
USGS	Halawa valley	1.00			
USGS	Moanalua RG1	**0.87**	1.00		
NCDC	Kaneohe	0.50	0.45	1.00	
HIMB	HIMB	0.49	0.46	**0.73**	1.00

USGS = U.S. Geological Survey;RG1 = Rain Gauge number 1; NCDC = National Climatic Data Center; HIMB = Hawaii Institute of Marine Biology.

(Fig. 2, panel A). While the other rainfall stations show high rainfall amount and consistently similar trends, the recorded rainfall of 2004 and 2005 at Moanalua rain gauge station is very low (Fig. 3). Statistical analysis indicates that stations on the leeward side (Halawa valley and Moanalua) have a stronger correlation compared to the windward side stations (Kaneohe and HIMB) (Table 1). However, all correlation values show statistical significance ($p < 0.05$). At the same time, as expected, there is a weak correlation between leeward and windward stations (Table 1), indicating less similarity in rainfall values between windward and leeward gauges. Such variations are expected to have an appreciable effect on the watershed hydrologic modeling and on the performance of watershed model and is an avoidable uncertainty introduced in the model.

Daily maximum and minimum temperatures as well as wind speed were obtained from the HIMB and Kaneohe stations. The HIMB station had additional daily data for solar radiation. The geographically closest available records of daily relative humidity were collected by the Western Region Climate Center (WRCC) (http://www.raws.dri.edu/wraws/hiF.html) at Oahu Schofield East and Oahu Forest National Weather Research (NWR). A WatchDog 2000 Series (Spectrum Technologies, Inc.) weather station was deployed for two years (2012–2013) at a wetland located at the coastal plain of Heeia (Fig. 2, panel A), and is referred to hereafter as Heeia station.

Since a longer, continuous coverage of climatic data was available outside of the watershed boundary, a correlation analysis was performed among the data (temperature, wind speed, solar radiation, and relative humidity) from Heeia and those stations located outside the watershed. The purpose of the correlation analysis was to fill the aforementioned missing data in Heeia records. Those stations that had reasonable correlations ($r^2 >= 0.5$) for daily values were used to fill the missing data. For rainfall data, the recorded values at the four adjacent rain gauge stations of the watershed (Fig. 2, panel A) were directly used for model input. In addition, the missing values were filled based on the monthly rainfall contour map of the Oahu Island with a contour interval of 50 mm based on the rainfall atlas of Hawaii (Giambelluca et al., 2013).

For model parameter optimization, daily streamflow data recorded at the Haiku station (USGS gauging code: 16275000) and at the wetland flow sampling station were used. As streamflow data were not available at the coastal plain, total daily streamflows at the coastal plain were estimated based on discharge measurements at the stream entry point to the Heeia wetland (Fig. 2, panel A). Streamflow at the wetland station was measured using a Pygmy flow meter for stream stages ranging from 1 to 1.4 m, over the year corresponding to 0.2 to 1 $m^3 s^{-1}$ in the period from May to December 2013. During each measurement, multiple discharge readings were taken across the stream to cover every 0.25 m of the stream for which a cross section was also measured. A Solinst pressure depth sensor was installed to monitor the water level every 30 min for the same period. The recorded water level was converted to streamflow by the USGS processing software (Ronald L. Rickman, personal communication, 2015).

In order to estimate long term continuous streamflow data at the coastal plain, a scaling factor was derived between the gauged streamflow at the Haiku and the corresponding measured values at the wetland for the overlapping period. The scaling factor is biased because the measurements only covered low flow conditions and do not reflect variability of this relationship due to changes in surface runoff and recharge with rainfall, including land use and topography. However, due to the lack of appropriate data, the study opted to use the developed scaling factor at least to evaluate the simulated time evolution of daily streamflow at the downstream location. Based on the analysis, the stream discharge at the wetland entry was approximately 3 times the Haiku streamflow value. In addition, groundwater flow modeling studies for the watershed (K.

Ghazal, unpublished results, 2014) suggest a similar scaling factor. Hereafter, the downstream streamflow estimate location is termed "wetland station".

2.4. Model set-up

SWAT model was built up based on the available geospatial data (DEM, land use and soil maps) and the hydro-meteorological data. Using the DEM map (Fig. 2, panel A), the Heeia watershed up to its mouth was divided into 22 sub-basins (Fig. 2, panel D), and the sub-basins were further sub-divided into 1300 hydrological response units (HRUs), based on zero threshold values for land use, soil type, and slope class of the watershed. This enabled us to include these factors, which are critical in assessing river basin management practice studies. Because of high topographic variability, 5 slope classes (maximum number of classes in SWAT) of 0–10%, 10–25%, 25–40%, 40–70% and >70% were defined, based on literature slope classes of the area (Kako'o'oiwi, 2011). Additionally, though the area of the study site is small, the number of sub-basins (compared to SWAT default) was increased to further capture the topographic variability of the watershed. Better representation of the watershed's spatial variability is achieved with the increased number of sub-basins and thus HRUs. In addition, the use of zero threshold value for HRUs classification facilitates a better assessment of the effect of land use change on the water balance components, which requires high resolution land use representation. Such land use scenarios are considered as part of mitigation and adaptation techniques by the local community and include the conversion of the Heeia wetland into a taro plantation to better mitigate floods and reduce sediment yield (Kako'o'oiwi, 2011). While this study did not address that change because SWAT does not include such a land use category in its current database, we demonstrate that the model is applicable in this watershed and it can be used for that purpose if data for taro plantation characteristics become available.

2.5. Model calibration

Both manual and automatic parameter-optimization procedures were used in model calibration, with the latter utilizing the Sequential Uncertainty Fitting (SUFI2) algorithm, as implemented in SWAT Calibration and Uncertainty Program (SWAT-CUP) (Abbaspour et al., 2007). The manual calibration was performed to fine tune the calibrated parameters, particularly to obtain a reasonable agreement for various water balance components.

To carry out the calibration processes, the SWAT model simulation period was split into three segments, which encompass a warming-up period (2000–2001) to initialize the state variables of the system (e.g the soil moisture content), a calibration period (2002–2008), and a validation period (2009–2013). Seven years of streamflow records with a relatively high, normal, and low flow conditions were selected for the model calibration. Prior to calibration, a sensitivity analysis (SA) was performed using the Latin Hypercube-One-factor-At-a-Time (LH-OAT) technique as implemented in SWAT-CUP (Abbaspour et al., 2007). SA was carried-out only at the Haiku station considering that continuous observed daily streamflow data were only available there. The minimum and maximum values of the SWAT parameters were fixed based on the ranges given in SWAT and SWAT-CUP (Abbaspour et al., 2007; Arnold et al., 2011). However, relative change (global multiplier) to the original values were used for a number of parameters that are spatially variable based on land use, soil type, and slope value. These include surface runoff curve number (CN2), soil water holding capacity (SOL_AWC), saturated soil hydraulic conductive (SOL_K), and maximum canopy storage (CANMX). Then, the SWAT model was calibrated using the parameters to which the model showed high sensitivity.

2.6. Model performance evaluation

Model calibration and validation should include multiple statistical evaluation criteria, considering that the single statistical metrics only evaluates a specific part of model performance (Moriasi et al., 2007). The SWAT model performance was evaluated through graphical comparison and by concurrently using six statistical criteria for goodness-of-fit: the Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970), the percent bias (PBIAS) (Moriasi et al., 2007), the root mean square error (RMSE) (Sorooshian et al., 1993), the RMSE-observation standard deviation ratio (RSR) (Moriasi et al., 2007), the Mean Bias Error (MBE) (ASCE, 1996) and the correlation coefficient (r) (Legates and McCabe, 1999).

2.7. Climate change scenarios

In this study, climate change scenarios were run based on the Intergovernmental Panel on Climate Change Special Reports on Emission Scenarios (IPCC, 2007), and previous climate change studies and statistical downscaling for the Hawaiian Islands (Timm and Diaz, 2009; Diaz et al., 2011; Timm et al., 2011). The atmospheric concentration of carbon-dioxide is expected to rise to levels between 550 ppm (B1 emission scenario) and 970 ppm (A1F1 emission scenario) (IPCC, 2007). It should be pointed out here that this study utilized the IPCC (2007) report, the only available (during the study time) and statistically downscaled climate change ranges, which considered the Hawaiian local climate conditions, interactions, and topographic features.

For an A1 B emission scenario, studies on climate change for Hawaii generally estimate a 10% decrease and 5% increase in monthly rainfall for wet season (November to April) and dry season (May to October), respectively (Timm and Diaz, 2009). The rainfall data of fourteen years (2000 to 2013) were perturbed to reflect these changes. The rainfall values were

Table 2
SWAT parameter sensitivity to daily streamflow at the Haiku station. Acronyms are explained in Table 3.

Parameter	t-stat	p-value	Parameter	t-stat	p-value
CN2	−50.247	0.000	REVAPMN	−1.467	0.143
CH_K2	26.276	0.000	GWQMN	1.263	0.207
ALPHA_BF	−15.732	0.000	SURLAG	1.213	0.226
ESCO	−4.936	0.000	SLSOIL	−0.776	0.438
CH_N2	3.595	0.000	HRU_SLP	−0.667	0.505
SOL_K	−3.464	0.001	SOL_Z	0.478	0.633
CANMX	2.204	0.028	RCHRG_DP	−0.448	0.655
OV_N	2.065	0.039	GW_REVAP	0.202	0.840
SLSUBBSN	1.982	0.048	SOL_AWC	−0.157	0.875
EPCO	1.968	0.050	GW_DELAY	−0.137	0.891

increased or decreased by multiplying by factors with a value of one means no change. During the dry season, a value of 1.05 was used, indicating 5% increase in rainfall compared to the historical data. Similarly, a change value of 0.9 was used during the wet season to reflect 10% decrease in rainfall amount compared with baseline values. The perturbation values were implemented in SWAT's sub-basin input files (Arnold et al., 2011). Also, studies of temperature trends on the Hawaiian Islands suggest that temperature is expected to increase by $\sim$1 °C by the end of 21st century (Diaz et al., 2011; Safeeq and Fares, 2012). Accordingly, the daily minimum and maximum temperature were increased in SWAT's sub-basin files for the period from 2000 to 2013. Additionally, to assess the effect of increase in CO_2 concentration on evapotranspiration and other water balance components, this concentration was increased from the default value of 330 ppm, signifying no climate change effect (Neitsch et al., 2011), to 550 ppm (for B1 emission scenario). The effect of CO_2 concentration change on evapotranspiration manifests through the plant canopy resistance term of the Penman-Monteith method, which is calculated as a function of leaf area index (LAI) and maximum effective leaf stomatal conductance (Neitsch et al., 2011). The maximum effective leaf conductance is estimated based on CO_2 value relative to the reference value of 330 ppm.

Three scenarios were formulated to illustrate the relative impact of the change of each climate variable on the water balance components. Scenario S1 only considers the seasonal change in rainfall. Scenario S2 has the same rainfall as S1 but also accounts for future temperature changes. Finally, scenario S3 combines rainfall, temperature, and CO_2 concentration changes.

3. Results and discussion

Initial calibration of the streamflow at Haiku station showed that, when the SCS-CN method was used, SWAT significantly overestimated peak flows. In addition, decreasing the curve number at moisture condition II (CN2), even by 50% of the default values, as well as modifying other surface runoff related parameters, did not improve the performance of the model and resulted in a negative NSE (-0.92). The model performance was substantially improved by modifying SWAT's source code to double the initial abstraction (I_a) from 0.2S to 0.4S, where S represents the potential maximum soil retention. Such a modification was justified considering the unique soil properties (e.g., high soil permeability) of the study site, which is characterized by high initial infiltration capacity and low surface runoff (Lau and Mink, 2006). The results presented in this study are based on the modified SWAT model.

3.1. Sensitivity analysis

The sensitivity analysis (Table 2) shows that, in general, CN2, CH_K2, ALPHA_BF, ESCO, SOL_K, CANMX, CH_N2, OV_N, SLSUBBSN, and EPCO are the most sensitive and important parameters for the watershed, as they show larger absolute values of t-statistics and their *p*-values are significant at 5% level of significance (see Table 3 for parameters description). The most sensitive parameter is the SCS curve number at moisture condition II (CN2), followed by the effective hydraulic conductivity of the main channel (CH_K2) (Table 1). The high sensitivity regarding CN2 was expected as it is the primary parameter that influences the amount of runoff generated from HRUs. The saturated soil hydraulic conductivity (SOL_K) that controls the lateral flow contribution to streamflow is also an important parameter. This should be expected because the watershed is dominated by forested land use and highly permeable volcanic soils with steep topography and lateral flow contribution is higher in the mountainous parts of the watershed. It is noticed that the base flow recession factor (ALPHA_BF) that could affect the shape of streamflow hydrograph, is identified as a parameter with a third sensitivity rank. This could be partly explained by the quick recession and steep nature of the streamflow hydrograph due to presence of dikes in the shallow aquifers of the mountainous area (Izuka et al., 1993), which is the specific characteristics of the Hawaiian watersheds. The soil evaporation compensation factor (ESCO) and channel Manning's roughness coefficient (CH_N2) are found to be the 4th and 5th ranked parameters, respectively. Such parameters could affect the surface runoff processes, evapotranspiration, and the shape of streamflow hydrograph. Although the surface runoff lag coefficient parameter (SURLAG) is usually identified as the most sensitive parameter for SWAT models of large-scale continental watersheds (Gassman et al., 2007), this parameter does not play a significant role in the Heeia watershed. This is probably due to the small-scale, steep, and flashy nature of the watershed that can cause most of the generated surface runoff to reach the watershed outlet in about one day. Thus, the

Table 3
Optimized parameter values for the Haiku and the wetland sub-watersheds.

Parameter	Description	Unit	Range	Calibrated	
				Haiku	Wetland
ALPHA_BF	Baseflow alpha factor	day^{-1}	0–1	0.001	0.016
CANMX	Maximum canopy storage[a]	mm	0–10	4.0–8.0	4.0–8.0
CH_K2	Effective hydraulic conductivity in main channel	mmh^{-1}	0–500	195.05	48.90
CH_N2	Manning's rougness coefficient		0–1	0.03	0.03
CN2	Curve number at moisture condition II[b]		35–98	35–62	37–79
ESCO	Soil evaporation compensation factor		0.1–1	0.36	0.85
EPCO	Plant transpiration compensation factor		0.1–1	1.00	0.20
GW_DELAY	Groundwater delay	day	0–100	51.55	78.45
RCHRG_DP	Groundwater recharge to deep aquifer		0–1	0.05	0.01
GW_REVAP	Groundwater revap coefficient		0.02–0.2	0.03	0.06
GWQMN	Minimum depth for groundwater flow ocurrence	mm	0–5000	451.80	417.67
REVAPMN	Minimum depth for groundwater revap ocurrence	mm	0–500	85.02	64.09
SOL_Z	Soil depth[c]	mm	0–3500	630–2038	1073–2100
SOL_K	Saturated soil hydraulic conductivity[c]	mmh^{-1}	0–2000	26–77	21–86
SOL_AWC	Soil water available capacity[c]		0–1	0.12–0.21	0.11–0.28
SURLAG	Surface runoff lag coefficient	day	0–10	1.50	1.50

[a] Varies with land use, but urban land use is zero.
[b] Varies with land use, soil & slope.
[c] Varies with soil type.

surface runoff lag is not relevant for such watershed and the lower sensitivity of the SURLAG parameter clearly reflects this behavior (Table 2).

3.2. Streamflow calibration

Overall, the estimated SWAT parameter values are physically reasonable for the watershed (Table 3). For example, the SURLAG is close to one as expected because the watershed is small and the time of concentration is around one day so that most of the surface runoff could reach the main channel on the day it is generated (Green and van Griensven, 2008). The CN2 parameter is relatively elevated in the downstream part of the basin, which could be related to intensive urbanization in that part of the watershed. However, the derived curve number values with the streamflow data are relatively low compared to reported values (Gassman et al., 2007), but are consistent with the study of Lau and Mink (2006). Since the upstream part is mostly covered by forest, the water use from the deeper soil profile is expected to be high in forest-covered land (Strauch and Volk, 2013). The higher EPCO and lower ESCO values in the upstream part of the watershed clearly illustrate this effect.

The ALPHA_BF value at Haiku station is 0.007 as estimated by the baseflow filter program (Arnold and Allen, 1999). However, during the calibration process, it was found that if this value is directly used for the upstream of Haiku, the simulated low flows slowly receded compared to observations. This indicates that the ALPHA_BF value obtained from baseflow filtering is too high and appeared to be inappropriate for SWAT, providing poor calibration. The calibrated value in the upstream of Haiku as shown in Table 3 of 0.001 is considerably lower than 0.007. The discrepancy between the value derived by baseflow filter program and SWAT may be due to the empirical nature of the former method and its lack of realistic representation of the watershed characteristics (Furey and Gupta, 2001; Leta, 2013; Leta et al., In press). The filter cannot, for example consider the presence of recurrent dikes in the shallow aquifer of the upstream part (Izuka et al., 1993) that essentially act as a natural barrier to baseflow and significantly reduce the groundwater flow to stream reach. In contrast, SWAT is physically based where the parameter values that represent the processes are expected to be well estimated (Migliaccio and Chaubey, 2008). According to Izuka et al. (1993), the upstream part of Heeia has more dikes in the shallow aquifer but these are not prevalent in the downstream part of the watershed. This can cause slow response to groundwater recharge. Consequently, the shallow aquifer groundwater slowly discharges into stream resulting in a slower depletion of groundwater and longer baseflow days (Okuhata, 2015). The lower ALPHA_BF value in the upstream part of the watershed likely reflects this effect.

3.3. Annual water balance

The annual observed and simulated water balance components for the calibration period (2002–2008) are summarized in Table 4 for the Haiku and the wetland stations. The observed total streamflow was divided into surface and baseflow using a baseflow filter program (Arnold and Allen, 1999). Note that the baseflow of Table 4 includes the lateral flow.

When compared to observations, the simulated water balance components in the upper watershed were overestimated even after the model code modification for I_a. This could be partly explained by the soil properties of rock outcrops, which cover 23% of the modeled area. For this soil type, the SSURGO database reported zero available water holding capacity (SOL_AWC in SWAT). However, for the same soil type, Safeeq and Fares (2012) reported a water holding capacity of 0.42 at field capacity (FC) and 0.34 at wilting point (WP), indicating that the SOL_AWC of rock outcrop is actually different from zero. This observation is also reasonable as the area is covered by shrubs and grassland. Accordingly, when the SOL_AWC, which

Table 4
Average annual observed and simulated water balance components (in mm) for the calibration period (2002–2008) at the Haiku and the wetland stations sub-watersheds.

Station	Type	Rainfall	Streamflow	Surface runoff	Baseflow	Evapotranspiration
Haiku	observed	3106	994	237	758	
	simulated		1259	223	981	1468
	PBIAS[%]		29	−13	44	
Wetland	observed	2217	972	296	675	
	simulated		958	290	644	1094
	PBIAS[%]		−1	−1	−5	

is the difference between FC and WP was set to 0.08 (= 0.42 – 0.34) and the model re-ran for the calibration process, results improved significantly. For example, the NSE almost doubled from 0.34 to 0.54. Also, peak flows, which were overestimated in the previous scenario, were now significantly decreased. As the SOL_AWC value obtained from the literature provides more reasonable hydrograph and water balance components, this value was used in further analysis.

For the Haiku station, while the surface runoff (SR) is underestimated by the model, the baseflow (BF) is considerably overestimated (PBIAS of 44). The overestimation of BF could be related to groundwater withdrawal at the rate of ca.1300 $m^3\ d^{-1}$ in upstream of the Haiku station, which was not taken into account in the model. In addition, as it was discussed earlier, the overestimation might be due to the empirical nature of the baseflow filter program that lacks realistic representation of the watershed characteristics, in contrast to the SWAT results, which are estimated by simulating physically based watershed processes. However, the total streamflow (SF) is still overestimated with a positive model bias of 29%. At the wetland station, the water balance components are well represented by the model. Comparable model performance is reported for the validation period.

For the watershed outlet, the SWAT simulated average annual subsurface flow component is 538 mm, which is 70% of the annual streamflow (773 mm), during the calibration period. As streamflow measurements were not available at the outlet of the watershed, the model results were compared with the filtered flow, which is 69% of total streamflow at the Haiku station. Furthermore, the fraction indicates that the subsurface flow contribution is larger than surface flow for the watershed. The simulated averaged annual streamflow (SF) of 773 mm approximately accounts for 41% of annual average rainfall (1900 mm), whereas the annual average actual evapotranspiration (AET) accounts for 52% (996 mm) during the calibration period. Though there were no available measured AET rates at our study site, our ET results were in line with rates reported for the Island of Oahu (Giambelluca et al., 2009; Safeeq and Fares, 2012). Also, the annual average rainfall contributes 27% (511 mm) to the groundwater system as recharge. The simulated recharge is close to the value (483 mm) reported by Engott et al. (2015) for the study area, although the latter estimated annual recharge based on synthetic daily rainfall values that were calculated by disaggregating monthly rainfall data. Overall, our simulated recharge is within the range (18–43%) of the findings reported for the Hawaiian Islands, as summarized by Safeeq and Fares (2012).

In general, the SWAT simulated water balance components are consistent with previous studies for the island, although those studies mainly focused on the dryer, leeward side. As the water balance components of the watershed are fairly represented by SWAT, it is concluded that the model is appropriate for different climate change scenario and management practice studies.

3.4. Daily streamflow

The calibrated and validated SWAT results of streamflow data at two gauging stations are provided in Table 5. The table also reports the goodness-of-fit statistics for different periods of calibration and validation in order to facilitate periods/events based model evaluation. However, for the sake of clear visualization, we will only discuss and show results for three years of streamflow hydrographs for both the calibration and the validation periods.

Generally, SWAT reasonably tracks the trends of the hydrograph and its temporal variability (Figs. 4 and 5). For the calibration period of the Haiku station, SWAT tends to underestimate some peak flows in the 2006 to 2008 period. On the other hand, the model simulates a number of peak values that are not consistent with the respective measured low values (Fig. 4, panel B). Additional calculations showed that some of the underestimated peak flows in certain periods cannot be corrected without further overestimating the certain peak flows between 2006 and 2008. Therefore, further calibrating and forcing the model under limited climate data would not provide fruitful results. Since there has been a negligible land-use change for the study period, it is concluded that the lack of consistent rainfall data causes these discrepancies in the model. As the model is very sensitive to rainfall input (Fig. 4), it is likely that the weak performance of the model for a certain period, including the underestimation of some peak and low flows, is due to a lack of well-represented rainfall amounts for the watershed. For example, the peak flow event of 2003, when the highest streamflow was recorded during the dry season, does not correspond to a peak rainfall event recorded in the neighboring watershed. Such a behavior is due to rainfall spatial variability over short distances, which did not enable the existing rain gauges to capture the local storms that caused the peak flow event of 2003. At the same time, in contrast to the calibration period, the model highly overestimated some peak flows of the validation period. This is clearly seen especially for the daily rainfall amount of approximately 200 mm d^{-1}

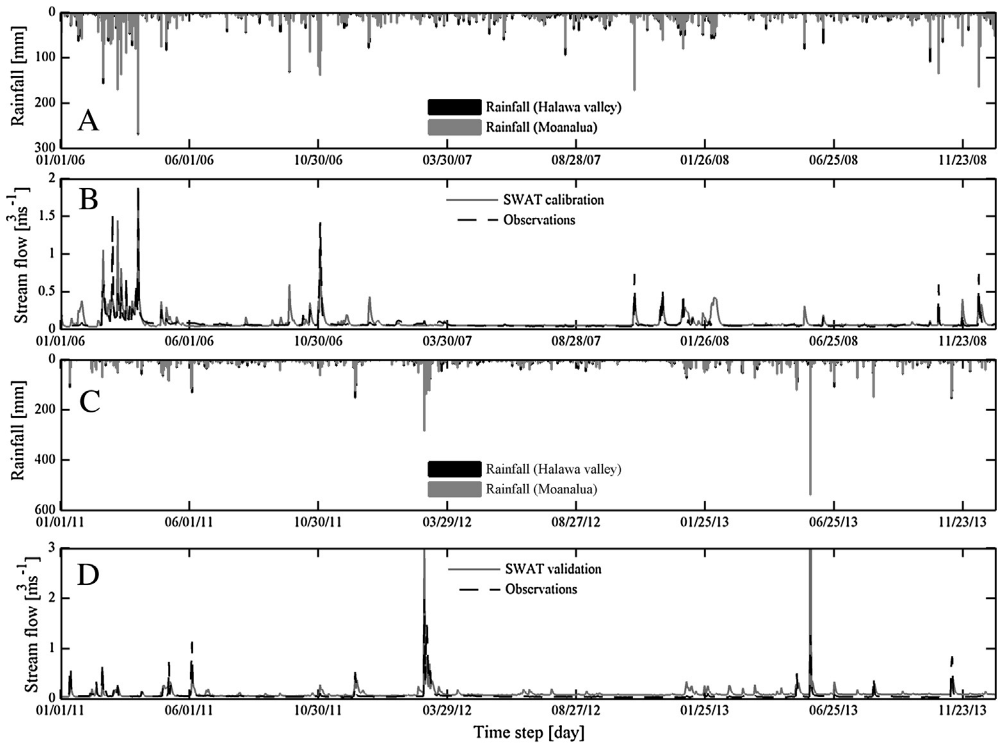

Fig. 4. The daily rainfall of 2006–2008 (A) and 2011–2013 (C), with the corresponding simulated and observed streamflows at Haiku during the calibration (B) and validation (D) periods.

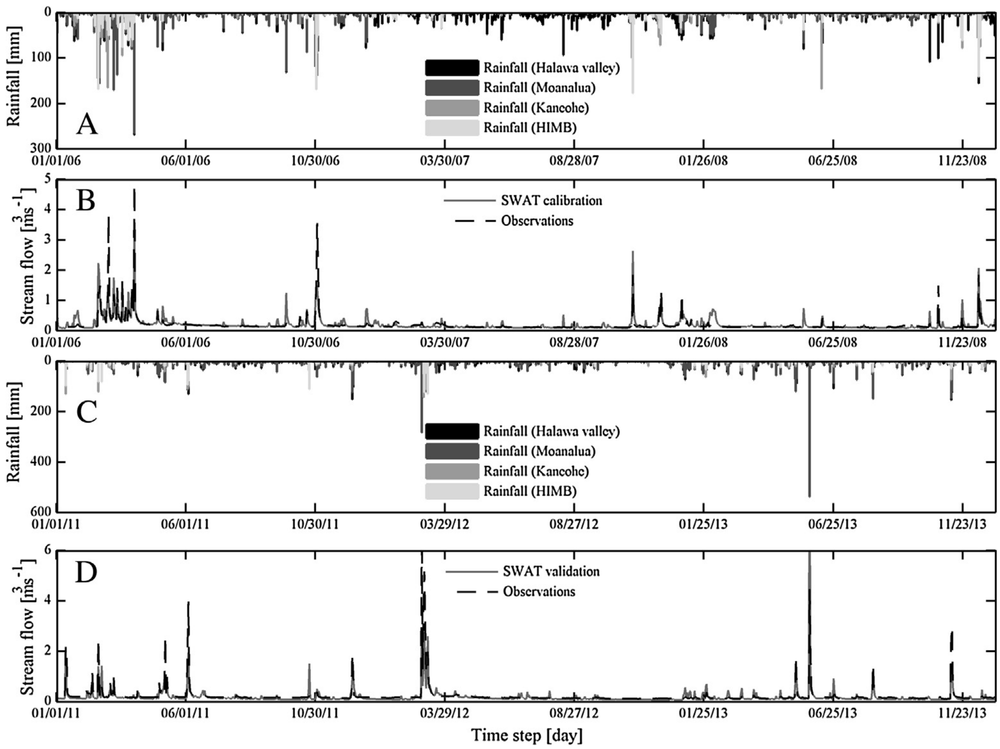

Fig. 5. The daily rainfall of 2006–2008 (A), and 2011–2013 (C) with the corresponding simulated and observed streamflows at the Heeia wetland during the calibration (B) and validation (D) periods.

Table 5
Goodness-of-fit statistics for the daily streamflow simulation at the Haiku and the wetland stations. The bold values represent overall performance.

Station	Period	time span	NSE	RSR	PBIAS[%]	RMSE[m^3/s]	MBE[m^3/s]	r
Haiku	Calibration	2002–2003	0.59	0.64	−49.56	0.08	−0.03	0.81
		2004–2005	0.44	0.75	−23.66	0.07	−0.02	0.71
		2006–2008	0.53	0.69	15.62	0.08	0.01	0.76
		2002–2008	**0.54**	**0.68**	**−13.17**	**0.08**	**−0.01**	**0.75**
	Validation	2009–2010	0.22	0.88	−21.44	0.09	−0.01	0.64
		2011–2013	0.39	0.78	45.89	0.09	0.04	0.75
		2009–2013	**0.35**	**0.81**	**25.24**	**0.08**	**0.02**	**0.67**
Wetland	Calibration	2002–2003	0.68	0.56	−42.34	0.18	−0.07	0.85
		2004–2005	0.52	0.70	−29.19	0.17	−0.06	0.77
		2006–2008	0.64	0.60	6.17	0.17	0.01	0.8
		2002–2008	**0.63**	**0.61**	**−17.22**	**0.17**	**−0.03**	**0.80**
	Validation	2009–2010	0.64	0.60	−30.86	0.22	−0.07	0.82
		2011–2013	0.41	0.77	−17.80	0.31	−0.04	0.71
		2009–2013	**0.49**	**0.71**	**−23.00**	**0.28**	**−0.05**	**0.74**

NSE = Nash-Sutcliff efficiency; RSR = root mean squared error to observation standard deviation; PBIAS = percent bias; RMSE = root mean squared error; MBE = mean bias error; r = correlation coefficient.

and above (Fig. 4, panel C). Consequently, a maximum daily streamflow of 320 mm d^{-1} is simulated by the model with a corresponding rainfall amount of 540 mm d^{-1}, while the observations show a maximum streamflow of 71 mm d^{-1} (Fig. 4, panel D).

In the downstream part of the watershed, the performance of the model is somewhat improved during the calibration period (Fig. 5, panel B). As compared to the Haiku station, the peak flows are well represented at the wetland station. In contrast to the Haiku validation, the wetland peak flows are systematically underestimated, except the peak flow event of 2013 (Fig. 5, panel D), which is caused by high rainfall amount (ca. 540 mm d^{-1}). But the results of the downstream part should be interpreted with caution as streamflows were derived from the application of a linear scaling factor to the Haiku streamflow observations. For example, the scaling factor bias for the observed peak flows is clearly seen in Fig. 5 where the observed peak flows are systematically overestimated as compared to the simulated ones. This suggests that the constant scaling factor of 3 might be high for the wet season's streamflows.

As it can be seen from Table 5, during the calibration period, the overall model performance for the daily streamflow simulation is "satisfactory" based on NSE values but "good to very good" for the other metrics (Moriasi et al., 2007). However, considering the period 2002 to 2003, while NSE is slightly increased at both stations, a lower performance is noticed in terms of PBIAS (Table 5), which is partly explained by a systematic underestimation of low flows of this period. It should be noted here that since NSE uses sum of squared residuals, it gives more weight to the difference in peak flows than low flows while PBIAS treats both values equally. Thus, the high NSE and PBIAS values in 2002 to 2003 (low flows dominated period) at both stations reflect such characterization despite the fact that the model systematically underestimates the low flows. At the Haiku station, a lower performance is also observed during the validation period (2009–2013), resulting in an "unsatisfactory" model performance in terms of NSE, which is mainly due to the overestimated peak flow events (Fig. 4, panel D). Nevertheless, based on Moriasi et al. (2007), the other statistical metrics still show "satisfactory to good" ranking except the PBIAS of 2011 to 2013 (Table 5).

In general, the low performance of the model for certain periods of calibration and validation could be related to the lack of a good quality and well represented rainfall data, a fact that has been well documented by Strauch et al. (2012). Evidence of low rainfall data quality for our case study is also clearly seen in Fig. 3. Fig. 3 clearly shows that the recorded rainfall amounts of 2004 and 2005 at Moanalua station are very low compared to the other stations. The Moanalua station has been operating since 1978 and is located in remote (mountain) area, it is suspected, thus, that this station might be old and poorly maintained. Incidentally, more than 80% of the Haiku sub-watershed used the rainfall data from this station. To correct for this, rainfall data for the period 2004 to 2005 were replaced by records from Halawa valley, which is located close to the Moanalua station in the mountainous area and also showed significantly strong correlation (Table 1). Such an action resulted in a much better representation of peak flows, which were severely underestimated when the recorded rainfall data from Moanalua were used.

Overall, findings suggest the suitability of SWAT for hydrological modeling of a small-scale, typical Hawaiian watershed, under scarcity of climate data. In addition, when compared to the large-scale continental watershed studies, the accuracy of our model was fairly comparable. For example, Ndomba et al. (2008a) reported similar performance for daily streamflows in terms of NSE for watershed from northeast Tanzania and linked the low performance of their model to scarcity of data. Mango et al. (2011) who used SWAT for both monthly streamflow simulations and climate-land use scenario analysis in Mara river basin (Kenya), reported negative NSE values when two nearby rain gauging stations were used. Nevertheless, their model performance was considerably improved when they used satellite-based estimated rainfall data. Although SWAT is commonly expected to show better performance for coarser time step (e.g., week, month), the monthly streamflow results of Mango et al. (2011) still indicate lower performance compared to our daily results. The latter contrast is encouraging and highlights the applicability of SWAT in Heeia watershed.

Table 6
Parameters of the three climate change scenarios.

Scenario	Rainfall (%)		Temperature (°C)	CO_2 (ppm)
	Wet season	Dry season		
S1	−10	5	–	330
S2	−10	5	1.1	330
S3	−10	5	1.1	550

Table 7
The minimum, maximum, and average relative change of annual water balance components relative to the baseline case. Bold values represent average relative change.

Scenario	Relative change [%]								
	Variable	Rainfall	SF	SR	LF	BF	Recharge	AET	PET
S1	Minimum	−5.8	−11.9	−16.9	−8.4	−12.3	−12.6	−1.5	0.0
	Maximum	−2.2	−3.4	0.4	−3.3	−4.9	−4.2	0.1	0.0
	Average	**−4.0**	**−7.7**	**−10.6**	**−5.4**	**−7.4**	**−7.3**	**−0.6**	**0.0**
S2	Minimum	−5.8	−13.8	−17.5	−8.6	−15.9	−16.6	−0.4	3.2
	Maximum	−2.2	−5.2	−1.1	−4.1	−6.9	−6.4	2.7	3.9
	Average	**−4.0**	**−9.4**	**−11.4**	**−6.1**	**−10.0**	**−10.0**	**1.0**	**3.5**
S3	Minimum	−5.8	−6.8	−15.8	−5.7	−4.2	−5.5	−5.4	−6.1
	Maximum	−2.2	0.6	3.6	−1.3	2.9	3.5	−3.6	−5.2
	Average	**−4.0**	**−3.4**	**−8.1**	**−3.4**	**−0.8**	**−0.8**	**−4.6**	**−5.6**

SF = Streamflow; SR = Surface Runoff; LF = Lateral flow; BF = Baseflow; AET = Actual Evapotranspiration; PET = Potential Evapotranspiration.

This study certainly confirms that additional and better rain and streamflow data are needed to improve the model to better represent some low and peak flows. The need for additional rainfall data is startling, considering the small size of the watershed that is characterized by a very strong rainfall gradient. However, assessing the relative response of the watershed's water balance components to various climate change scenarios are of great interest and should be valuable, even with modeling uncertainties.

3.5. Climate change scenarios

3.5.1. Annual water balance

Three climate change scenarios (S1, S2, and S3) as summarized in Table 6 were used to assess the sensitivity of water balance components to future predicted changes. In general, the predicted annual average water balance components decreased in comparison to the baseline, irrespective of the applied scenario (Table 7). The annual relative change also showed a decreasing trend, except for actual and potential evapotranspiration, which revealed a relative decrease or increase depending on the applied scenario. Hence, the annual water balance components are generally projected to decrease in the future. However, for a few years, the annual groundwater recharge is projected to increase (maximum of 4%) for scenario S3 (Table 7) because of the likely decrease in evapotranspiration. It can be concluded that the 10% decrease in rainfall during wet season and 5% increase during dry season are the main factor for the overall decrease in annual water budgets for this watershed.

3.5.2. Monthly water balance

Depending on the applied scenario, the monthly water balance components showed different responses in seasonal changes. For the S1 scenario, an increase of dry season rainfall by 5% and a decrease by 10% in wet season are expected to lead to a maximum decrease in surface runoff by 21% in January. Also, the largest both positive and negative changes are observed for the surface runoff component, followed by groundwater recharge (Fig. 6). This indicates the high sensitivity of surface runoff and groundwater recharge to rainfall input. Moreover, a more pronounced change in water budget is observed during the wet season (November to April), indicating a higher sensitivity of water balance components to rainfall change (Fig. 6). An interesting observation from Fig. 6 is that both streamflow and baseflow will consistently decrease for the S1 scenario, irrespective of the direction of the shift in seasonal rainfall change. This could be related to a larger decrease in rainfall during the wet season but an increase in AET during the dry season. Also reflected in this is the fact that the response of baseflow to rainfall change is significantly delayed by about two months, which has an impact on baseflow contribution to total streamflow. Overall, the decrease in baseflow and thus streamflow, is consistent with previous findings by Oki (2004) and Bassiouni and Oki (2013) who reported generally decreasing trends in historical streamflow in Hawaii, including the Heeia watershed. Of interest is the fact that climate change scenarios were run only for 14 years with findings that consistently agree with Safeeq and Fares (2012) who ran climate change scenarios for 43 years in the leeward side of Oahu. This shows that our impact assessment can provide useful information on water balance perturbation without accounting for long-term climate change projections despite data scarcity.

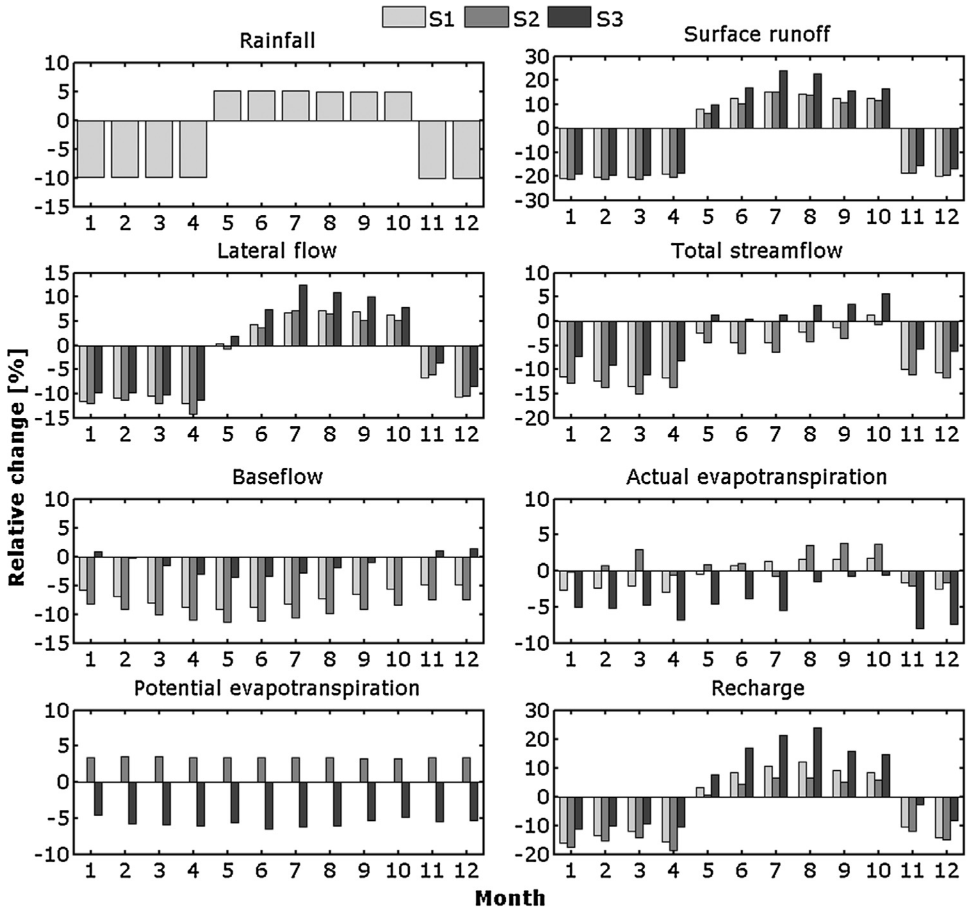

Fig. 6. Percent change in monthly water balance components as a result of climate change scenarios S1 (perturbed rain), S2 (rain & temperature), S3 (rain, temperature, & CO2) relative to the baseline.

For the S2 scenario, an increase in temperature is expected to cause a larger decrease in water balance components as a result of an increase in AET, especially during the dry season. For example, in April, a change in ET of −3% (for S1) vs −1% (for S2) resulted in a decrease in recharge of −16% and −19%, respectively. In comparison to the S1 scenario, a more pronounced change for both baseflow and groundwater recharge is observed for the S2 scenario (Fig. 6). Finally, the high sensitivity of baseflow to temperature change, and thus the considerable impact of evapotranspiration on the baseflow component, is clearly demonstrated by a larger % change in S2 in comparison to S1 (Fig. 6).

While similar directional changes can be observed for the S1 and S2 scenarios, elevated CO_2 concentrations are expected to considerably affect both potential and actual evapotranspiration. When the CO_2 emission of S2 is increased from 330 ppm to 550 ppm, a slight increase in streamflow is predicted during the dry season (Fig. 6). This is most likely due to a consistent decrease in actual evapotranspiration and plant leaf stomatal conductance (Safeeq and Fares, 2012). A noticeable increase in recharge is also predicted for the S3 scenario, particularly during the dry season (e.g., maximum 24% in August) as a consequence of a decrease in AET and small increase in rainfall.

4. Conclusions

Based on the available geospatial and hydro-meteorological data, a SWAT model was developed for the integrated river basin management of the Heeia watershed. Contrasting to mainland, large-scale continental watersheds, applications should reflect the watershed's small size, typical soil properties, and high topographic variability. In addition, a modification in the model is necessary to capture the unique volcanic soil properties that is characterized by a larger initial abstraction value than the value commonly utilized in model applications of continental watersheds.

A sensitivity analysis (SA) identified the top five sensitive parameters for the watershed, namely, SCS curve number at soil moisture condition II (CN2), main channel effective hydraulic conductivity (CH_K2), baseflow alpha factor (ALPHA_BF), channel Manning's roughness coefficient (CH_N2), and soil evaporation compensation factor (ESCO). Although a surface runoff lag coefficient (SURLAG) is commonly identified as a sensitive parameter in large scale continent watersheds, this parameter did not play an important role for the study site. Overall, the SA findings are consistent with the watershed characteristics.

The calibration and validation procedures estimated water balance components and daily streamflow that generally showed "satisfactory" model performance, though the model underestimated some peak flow events, including the low flows of a certain period. At the same time, the model simulated some peak flows that happened during intensive rainfall while the corresponding observed flows showed low values. The quality of existing rainfall data from the nearby stations is questionable and the use of such data may not adequately represent the local climate variability and distribution in the watershed. Thus, accounting for rainfall data variability is of paramount importance, which is startling considering the small size of the watershed in the order of 11.5 square kilometers. Further improvement in modeling can be achieved if good quality and well-represented climate data are used. Installation of hydro-meteorological stations to capture variability within the study site would help any future studies.

To illustrate the usefulness of the developed model, SWAT was then used for climate change impact assessment on water balance. The projected different climate change scenarios showed both increasing and decreasing trends in monthly water balance components except baseflow, which showed decreasing trend. However, it is expected that the net annual average water balance components will generally be negative, indicating more limited water availability for the Heeia watershed. The water balance components were more sensitive to rainfall change as compared to temperature change and increase in CO_2 concentrations. More importantly, the groundwater flow component will be negatively impacted by the projected rainfall and temperature changes. It is thus concluded that the projected scenarios may adversely affect the groundwater sustainability of the watershed and the ecological functioning of the riparian system.

Lastly, the adapted SWAT model together with the example application demonstrated the usefulness of the model, despite some limitations of climate data, as a tool for assessing water resources availability in the Hawaiian and similar islands, where volcanic outcrops exist, and climate and hydrological data scarcity commonly prevail. Further, assessing climate change scenarios provide useful information for evaluating the future freshwater availability and designing appropriate climate change mitigation measures. Relative response of the watershed to various climate change scenarios are valuable, even with modeling uncertainties.

Conflict of interest

The authors declare no conflict of interest.

Acknowledgments

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