Impact of climate change on future stream flow in the Dakbla river basin

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ABSTRACT

A systematic ensemble high-resolution climate modelling study over Vietnam was performed and future hydrological changes over the small catchment of Dakbla, Central Highland region of Vietnam, were studied. Using the widely used regional climate model WRF (Weather Research and Forecasting), future climate change over the period 2091–2100 was ascertained. The results indicate that surface temperature over Dakbla could increase by nearly 3.5 °C, while rainfall increases of more than 40% is likely. The ensemble hydrological changes suggest that the stream flow over the peak and post-peak rainfall seasons could experience a strong increase, suggesting risks of flooding, with an overall average annual increase of stream flow by 40%. These results have implications for water resources, agriculture, biodiversity and economy, and serve as useful findings for policy makers.

Key words | climate change, dynamical downscaling, hydrology, stream flow, Soil and Water Assessment Tool, WRF

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INTRODUCTION

Climate change impacts are studied using the information derived by global climate models (GCMs) which still remain the primary tools in understanding climate and climate change at a global scale. However, it has been realized that to study sub-global scales, i.e. continental, regional or sub-regional scales, the GCMs do not provide detailed information of climate as it is observed in reality. This is largely attributable to the coarse resolution of the GCMs, making them unsuitable for regional impact studies (Giorgi 1990). The need for regional scale information is also emphasized by the fact that GCM climate projections do not allow regional examinations such as water balances or trends of extreme precipitation due to their coarse grid resolution. This clearly applies to hydrological impact studies over a river basin, as most of the river basins of the world are smaller than the typical resolution (c. 300 km) of the GCM. Such hydrological models therefore need to be driven by high-resolution data for better assessments of regional scale impacts. The GCMs do not simulate precipitation, one of the most important and sensitive climate parameter highly variable in space and time, with adequate fine-scale details to be applied for regional-scale impact studies. When impact studies are performed, such as hydrology, regional-scale impact studies warrant high-resolution climate information. To this end, regional climate models (RCMs) (which are limited area models) at a higher resolution than that of GCMs (c. 10–50 km) are widely used in climate research. For hydrological studies it has become common to use the output of the regional climate models as input to hydrological models. Similar studies have been done by Hay *et al.* (2002); Sushama *et al.* (2006); Andersson *et al.* (2006) and Graham *et al.* (2007).

This paper describes such a method where the climate outputs (precipitation and surface temperature) from a high-resolution regional climate model (Weather Research and Forecasting or WRF) are applied to a hydrological model (Soil and Water Assessment Tool, SWAT) (Arnold *et al.* 1998) to study changes in future stream flow over the small river catchment Dakbla, over the Central Highland region of Vietnam. Ensemble scenarios of climate change derived from the WRF model driven by three different GCMs are described, all under the A2 emission scenario.

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Similar studies have also been documented by Hamlet & Lettenmaier (2000) and Wei & Watkins (2011).

STUDY AREA

The Dakbla River is a small tributary of the Mekong river over the Lower Mekong Basin (LMB) in southeast Asia. The catchment has a total area of 2,560 km^2 from the upstream to Kon Tum gauging station (Figure 1) and lies over the Central Highland region of Vietnam. The catchment is covered mostly by tropical forests which are classified as tropical evergreen forest, young forest, mixed forest, planned forest and shrub. The climate of this region follows the pattern of the Central Highland region in Vietnam with an annual average temperature of c. 20–25 °C and a total annual average rainfall of c. 1,500–3,000 mm with high evapotranspiration rates of c. 1,000–1,500 mm per annum. There are two main seasons for the Central Highland region: a rainy season from May through to October (referred to as MJJASO) and dry season from November through to April (referred to as NDJFMA). Flood season is around 1 month after the rainy season, because some buffer time is required to fill up the groundwater for basalt soil in this region after the earlier 6-month dry period. Due to the steep slope topography and heavy rainfall concentrations, stream flow in this region acquires a high velocity, especially during floods, causing massive damage to people and property. There is also a very high potential of constructing hydropower dams to store surface water for multipurpose needs: irrigation, electricity generation and flood control. Upper Kon Tum hydropower, with an installed capacity of 210 MW, has been under construction since 2009 (to be completed in 2014) in the upstream region of Dakbla river; at 110 km downstream, the Yaly hydropower plan has been constructed (installed capacity 720 MW; the second biggest hydropower project in Vietnam) which has been in operation since 2001. Forecasting stream flow mainly by using rainfall is therefore an important task in this region for both hydropower and irrigation.

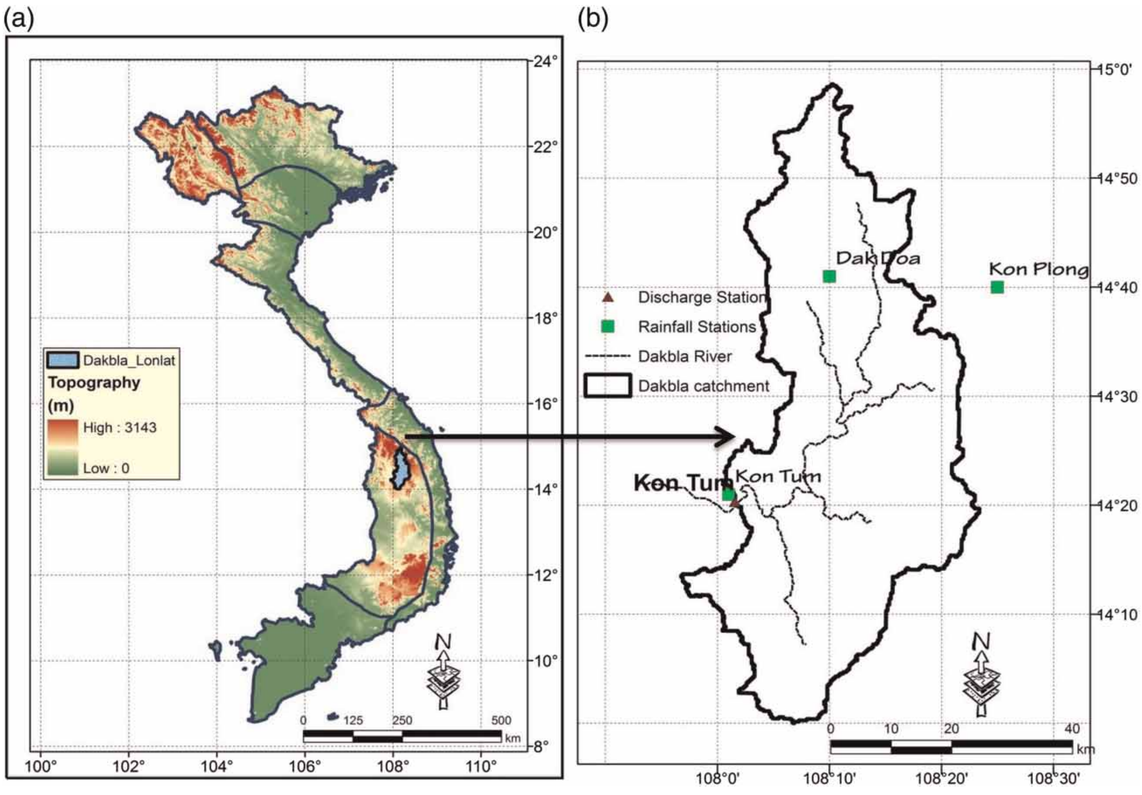

Figure 1 | Map of Vietnam climate zones and location of Dakbla catchment. (a) Different climate zones and topography of Vietnam; and (b) Dakbla catchment and its meteorological and river gauging station.

METHODS

Soil and water assessment tool (SWAT)

The rainfall–runoff model is a typical hydrological modelling tool that determines the runoff from the watershed basin resulting from rainfall falling on the basin. Precipitation is therefore an important input in deriving runoff in hydrological modelling. The SWAT model (Arnold *et al.* 1998), used for rainfall–runoff modelling in this study, was developed to quantify the runoff and concentration load due to the distributed precipitation, watershed topography, soil and land use conditions.

SWAT is a river basin scale model developed by the United States Department of Agriculture (USDA) Agriculture Research Service (ARS) in the early 1990s. It has been designed to work for large river basins over a long period of time. Its purpose is to quantify the impact of land management practices on water, sediment and agriculture chemical yields with varying soil, land use and management condition. SWAT version 2005 with an ArcGIS user interface (ArcSWAT) was used in this study. There are two methods for estimating surface runoff in SWAT model: Green & Ampt (2011) infiltration method, which requires precipitation input over a sub-daily scale and the Soil Conservation Service (SCS) curve number procedure (USDA Soil Conservation Service 1972) which uses daily precipitation. The latter was selected in this study for simulations, since daily rainfall from the climate models was used as input to the SWAT model. The retention parameter is very important in the SCS method and is defined by curve number (CN), a function of the soil permeability, land use and antecedent soil water conditions.

The SWAT model offers three options for estimating potential evapotranspiration (PET): Hargreaves (Hargreaves *et al.* 1985); Priestley–Taylor (Priestley & Taylor 1972) and Penman–Monteith (Monteith 1965). The Hargreaves method requires only maximum, minimum and average surface temperature. The Priestley–Taylor method needs solar radiation, surface temperature and relative humidity. The inputs for the Penman–Monteith method are the same as those for Priestley–Taylor; however, it also requires the wind speed. Due to limited available meteorological data for the site considered in this study, the Hargreaves method is applied.

In the SWAT model, the land area in a sub-basin is divided into what are known as hydrological response units (HRUs). HRUs are constructed through a unique combination of land use and soil information. One HRU is the total area of a sub-basin with a particular land use and soil characteristics. While individual fields with a specific land use and soil may be scattered throughout a sub-basin, these areas are lumped together to form a single HRU. These are used in most SWAT applications since they simplify a simulation by putting together all similar soil and land use areas into one single response unit (Neitsch *et al.* 2004). All parameters such as surface runoff, PET, lateral flow, percolation, soil erosion, nitrogen and phosphorus are measured in each HRU.

Model set-up

Ensemble regional climate model outputs were used as input to the SWAT hydrological model to determine future hydro-climatic changes. These regional climate model outputs (surface temperature and precipitation) were derived using the WRF model which was used to downscale the GCMs CCSM3.0, ECHAM5 and MIROC-medres, all forced under the Intergovernmental Panel on Climate Change (IPCC) A2 future greenhouse gas emission scenario. This regional climate model was initially driven by the ERA40 reanalysis which refer to the ‘true’ climate period of 1981–1990. Later, the WRF model was also driven by the GCMs CCSM3.0, ECHAM5 and the MIROC-medres for both the present day (1981–1990) and the future (2091–2100) climates. For simplicity, the simulations of WRF driven by ERA40 reanalysis and the GCMs CCSM3.0, ECHAM5 and the MIROC-medres are referred to as WRF/ERA, WRF/CCSM, WRF/ECHAM and WRF/MIROC, respectively.

For comparison of WRF model simulated precipitation and surface temperature profiles, two sets of gridded observational datasets are used: CRU (Climatic Research Unit, University of East Anglia, UK, 0.5° data) and the APHRODITE (Asian precipitation highly resolved observational data integration towards evaluation of water resources) (0.25° data) from the Japanese Meteorological Agency (JMA). In this paper, the latter is referred as APH. These datasets have been documented by Mitchell & Jones (2005) and Yatagai *et al.* (2012), respectively.

For hydrological simulations, daily precipitation data were obtained from three rainfall stations (Kon Tum, Dak Doa and Kon Plong; the former two lie inside and the latter outside the Dakbla catchment) and daily river stream flow data were taken from the gauging station at Kon Tum, all shown in Figure 1(b). Surface temperature, rainfall and discharge data have been acquired for the two periods 1980–1990 and 1995–2005, at a daily rate. For use in the SWAT model, the digital elevation model (DEM) of 250 m was obtained from the Department of Survey and Mapping (DSM), Vietnam. The land use map was obtained from the Forest Investigation and Planning Institute (FIPI) and the soil map was obtained from the Ministry of Agriculture and Rural Development (MARD), both in Vietnam (Figure 2).

A couple of benchmarking indices were used to assess the performance of the SWAT model: Nash–Sutcliffe Efficiency (NSE) proposed by Nash & Sutcliffe (1970) and the coefficient of determination (R^2). The value of NSE ranges from minus infinity to 1 while R^2 is from 0 to 1, with 1 representing a perfect match for both indices. The NSE is considered to be the most appropriate relative error or goodness-of-fit measures available, due to its straightforward physical interpretation (Legates & McCabe 1999).

RESULTS AND DISCUSSION

Daily precipitation data were obtained from the three rainfall stations (Kon Plong, Kon Tum and Dak Doa) for the periods 1980–1990 (calibration) and 1995–2005 (validation). Daily maximum and minimum surface temperature data were also obtained from the local authority from the Kon Tum meteorological station for the same period. Daily river stream flow data were obtained from the Kon Tum gauging station at the downstream end of the Dakbla River. These data were used for both the calibration and validation processes in the stream flow simulations of the SWAT model. In the calibration part, the SWAT model was run in a daily time step for the period of 1980–1990 using observed rainfall and river stream flow at Kon Tum gauging station, with the first year 1980 used as the spin-up period. The validation was performed for the 10-year period of 1996–2005 to ensure that the model was well calibrated. The reason for choosing these 10-year periods for calibration and validation is because of the data availability; longer-period data spanning 30 years were not available from station sources.

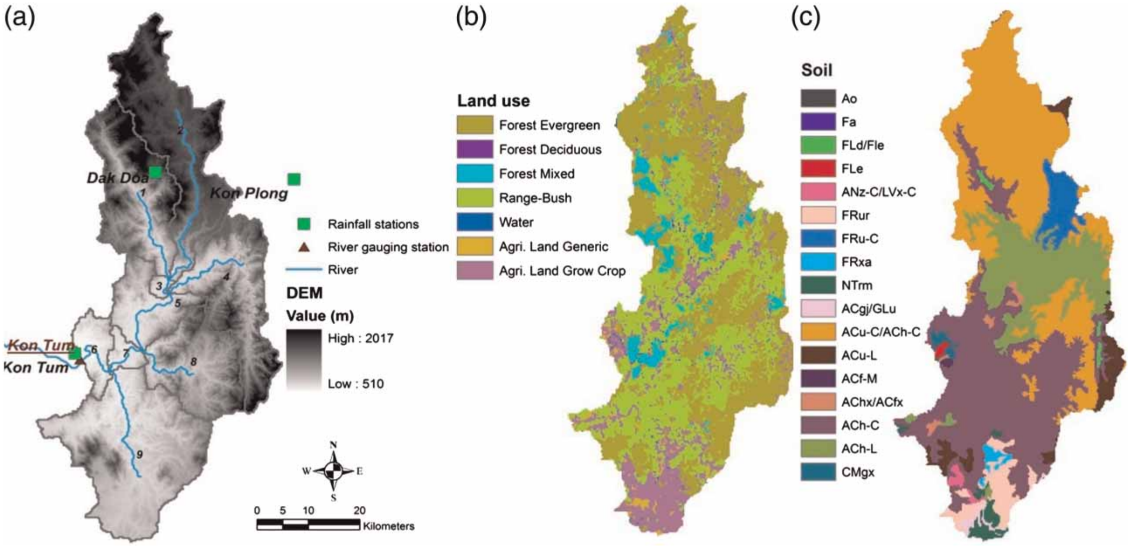

Figure 2 | SWAT model spatial inputs: (a) DEM; (b) land use; and (c) soil map of Dakbla river basin.

A sensitivity analysis was conducted prior to calibrating the hydrological model. This is a method that analyzes the sensitivity of the different model parameters (Table 1) that influence the hydrological model performance. This method serves to filter out those model parameters that do not have a significant influence on the model results. On the other hand, it also aims to reduce the number of parameters required in the auto-calibration method.

Traditional methods of sensitivity analysis have been classified by Saltelli *et al.* (2000). They are: (1) local method (Melching & Yoon 1996); (2) integration of local to global method using random one-factor-at-a-time (OAT) proposed by Morris (1991); and (3) global methods such as Monte Carlo and Latin-Hypercube (LH) simulation (McKay *et al.* 1979; McKay 1988). By studying the advantages and disadvantages of each of the above methods, van Griensven & Meixner (2006) developed the LH-OAT method which performs LH sampling followed by OAT sampling. This method samples the full range of all parameters using LH design along with the precision of OAT sampling to ensure that the changes in each model output could be attributed to the changed parameter. In this study, the LH-OAT design was coupled to the ArcSWAT 2005 model for the sensitivity analysis module. In the SWAT model there are 25 parameters that are sensitive to stream flow, six parameters sensitive to sediment transport and nine other parameters sensitive to water quality. In this study, sensitivity analysis was performed for the 25 parameters of stream flow as listed in Table 1, from which 11 most sensitive parameters were then selected (Table 2) for performing the auto-calibration.

Since the ArcSWAT model has the options to choose either manual or auto-calibration, calibration is applied to the most sensitive parameters to yield the optimal set of values for the model parameters which results in the minimum discrepancy between the observed and the simulated river discharge data. Parameter solution method (ParaSol) is a built-in auto-calibration model in the ArcSWAT 2005 version (van Griensven & Meixne 2004) which was used

Table 1 | SWAT parameters sensitive to stream flow

Group	Parameter	Description	Unit
Soil	Sol_Alb	Moist soil albedo	–
	Sol_Awc	Available water capacity	mm mm^{-1}
	Sol_K	Saturated hydraulic conductivity	mm h^{-1}
	Sol_Z	Depth to bottom of second soil layer	mm
Subbasin	Tlaps	Temperature laps rate	$^{\circ}$C km^{-1}
HRU	Epco	Soil evaporation compensation factor	–
	Esco	Plant uptake compensation factor	–
	Canmx	Maximum canopy storage	mm H_2O
	Slsubbsn	Average slope length	m
Routing	Ch_N2	Manning's n value for the main channel	–
	Ch_K2	Effective hydraulic conductivity in main channel alluvium	mm h^{-1}
Groundwater	Alpha_Bf	Baseflow alpha factor	days
	Gw_Delay	Groundwater delay	days
	Gw_Revap	Groundwater 'revap' coefficient	–
	Gwqmn	Threshold depth of water in the shallow aquifer for return flow to occur	mm H_2O
	Revapmn	Threshold depth of water in the shallow aquifer for 'revap' to occur	mm H_2O
Management	Biomix	Biological mixing efficiency	–
	Cn2	Initial SCS runoff curve number for moisture condition II	–
General data basin	Sftmp	Snowfall temperature	$^{\circ}$C
	Smfmn	Minimum melt rate for snow during year	mm H_2O $^{\circ}$C^{-1} day^{-1}
	Surlag	Surface runoff lag time	days
	Timp	Snow pack temperature lag factor	–
	Smfmx	Maximum melt rate for snow during year	–
	Blai	Maximum potential leaf area index for land cover/plant	–
	Slope	Slope	–

Table 2 | Sensitivity analysis ranking of 11 most sensitive parameters in SWAT model to stream flow

Sensitivity analysis order	Parameter	Description	Parameter range	Initial value	Optimal value
1	Cn2	Initial SCS runoff curve number for moisture condition II	35–98	35	96.78
2	Ch_K2	Effective hydraulic conductivity in main channel alluvium	–0.01 to 500	0	150
3	Sol_Awc	Available water capacity	0–1	0.22	0.44
4	Sol_K	Saturated hydraulic conductivity	0–2,000	1.95	1,873
5	Ch_N2	Manning's n value for the main channel	–0.01 to 0.3	0.014	0.073
6	Alpha_Bf	Baseflow alpha factor	0–1	0.048	0.027
7	Surlag	Surface runoff lag time	1–24	4	1
8	Esco	Plant uptake compensation factor	0–1	0	0.66
9	Gwqmin	Threshold depth of water in the shallow aquifer for return flow to occur	0–5,000	0	1,107
10	Gw_Revap	Groundwater 'revap' coefficient	0.02–0.2	0.02	0.17
11	Gw_Delay	Groundwater delay	0–500	31	215

in this study for auto-calibration of the SWAT model. This ParaSol method has also been documented by van Griensven & Meixne (2004). Using the above methodology, the SWAT model was calibrated to ensure a robust performance before undertaking stream flow simulations using the regional climate model output. The R^2 and the NSE index were used as benchmarking indices to assess the goodness-of-fit of the SWAT hydrological model.

The calibration and validation graphical results for Dakbla River are shown in Figures 3 and 4 at (a) daily and (b) monthly scales, respectively. It is clearly seen in the calibration that the simulated peak-to-peak discharge (on a monthly scale) and the low flow agree well with the observed data better than the agreement seen on daily scale, due to a higher variability in daily scales. The validation plots indicate that the trend of observed data is being captured by the simulated flow, although some of the peak-to-peak discharges are underestimated compared to observed flow. The values of R^2 and NSE shown in Table 3 indicate that the comparison indices over a daily and monthly scale for both calibration and validation are around 0.5 and 0.7, respectively. These values indicate a good performance of the SWAT model (Santhi *et al.* 2001) and that the hydrological model was well calibrated using the ParaSol method. Since the model was able to reproduce the pattern of the observed stream flow well enough, the next stage of the application of the regional climate model derived data (precipitation and surface temperature) to be used for stream flow simulations is discussed, as the calibration and validation stages used only the station data precipitation and surface temperature.

Before discussing the stream flow results of the SWAT model, the WRF model simulated climates is useful to highlight the usefulness in applying RCM results for hydrological applications. The comparison of WRF model simulated profiles of present-day surface temperature over Dakbla region and the gridded observation datasets CRU and APH is displayed in Figure 5. It is notable that, even between the CRU and APH observations, CRU exhibits hotter profiles than the APH dataset. Nevertheless, the WRF model results show a reasonable simulation of the model by exhibiting a good pattern of temperature gradients as well as their magnitudes. The simulations of WRF/ECHAM, WRF/CCSM and WRF/MIROC also show similar profiles to that of WRF/ERA. Figure 6 shows the WRF model precipitation distribution over Dakbla catchment for the present-day climate compared against the two gridded observational datasets. The WRF/ECHAM shows overestimation in rainfall over this region, while WRF/CCSM and WRF/MIROC share similar distributions to that of WRF/ERA and APH. It can be stressed here that while surface temperatures are more homogeneous and easy to be simulated, precipitation is rather difficult to simulate well. Detailed evaluation of the model performance was carried out (not discussed

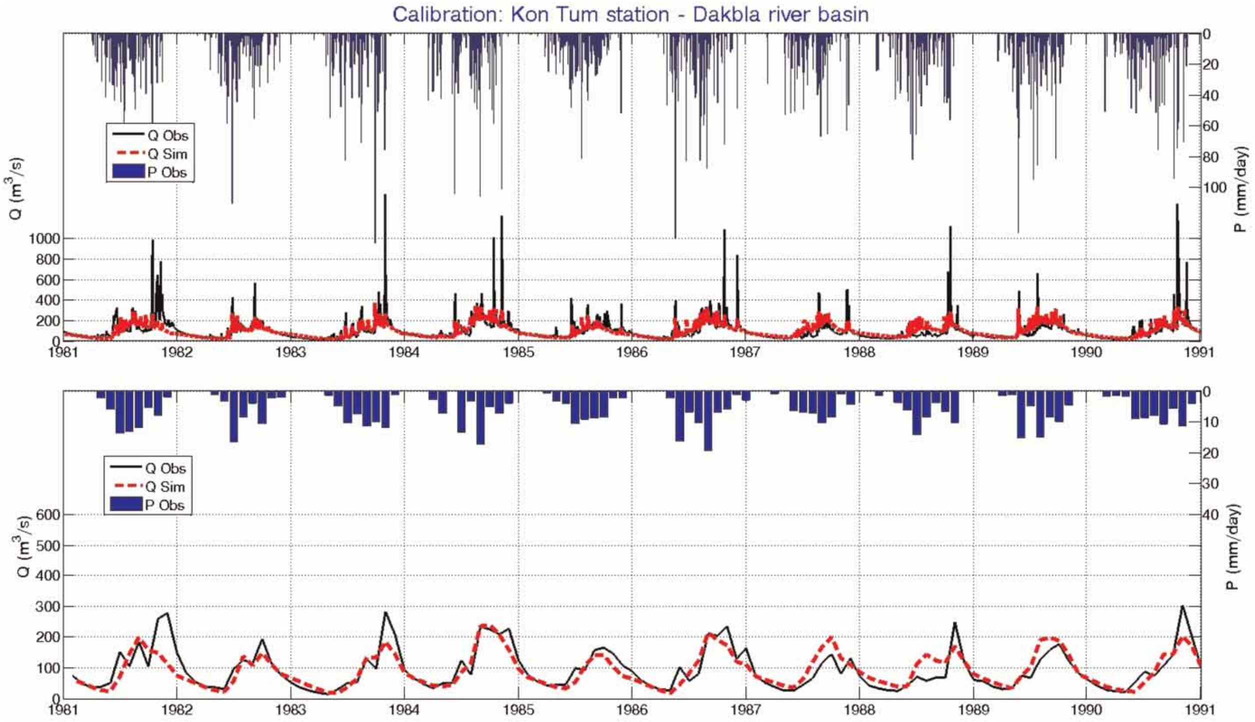

Figure 3 | Calibration of the SWAT model, top: daily scale and bottom: monthly scale.

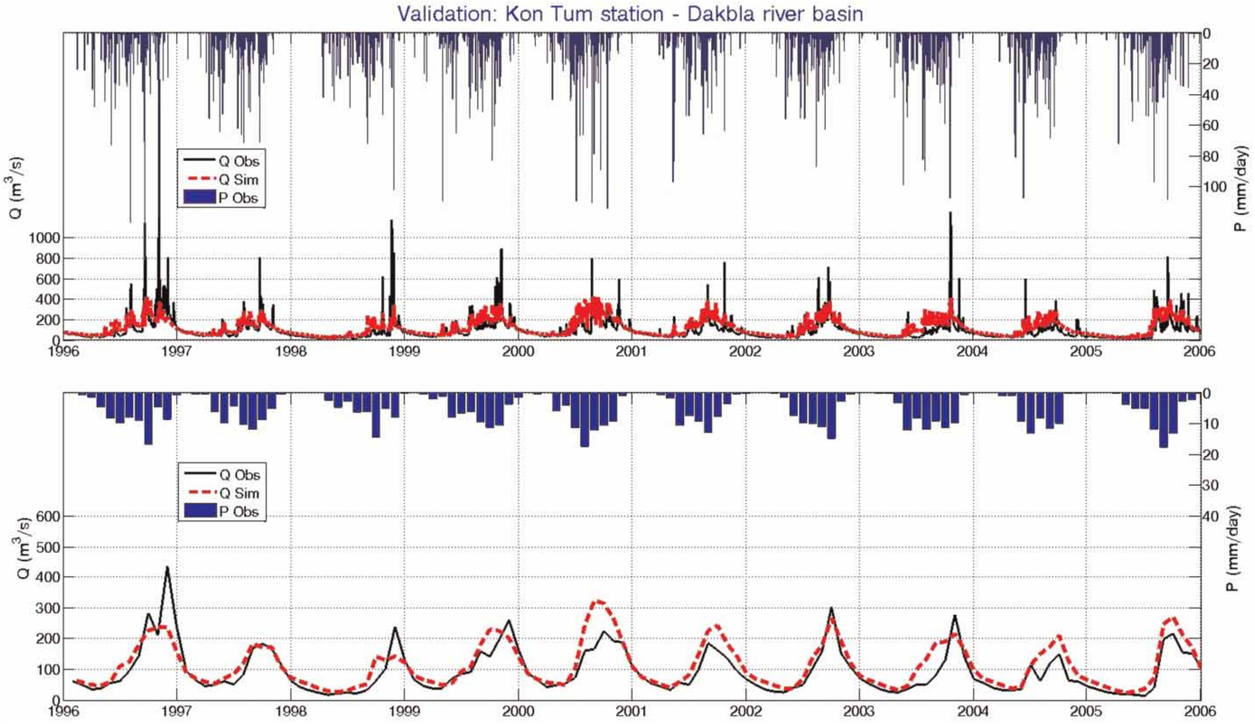

Figure 4 | Validation of the SWAT model, top: daily scale and bottom: monthly scale.

Table 3 | Statistical indices of SWAT Dakbla river basin model calibration and validation: R^2 and NSE

Calibration (1981–1990)				**Validation (1996–2005)**			
Daily		**Monthly**		**Daily**		**Monthly**	
R^2	**NSE**	R^2	**NSE**	R^2	**NSE**	R^2	**NSE**
0.58	0.53	0.72	0.74	0.45	0.43	0.73	0.66

here), but is outwith the scope of this paper. These results are merely a bird's eye view of regional climate simulations over a small region such as that of Dakbla. The climate model results are shown to substantiate the use of model-derived climate variables for further use in the SWAT hydrological simulations.

The precipitation and surface temperature variables from the RCM outputs of WRF/ERA were initially used for stream flow simulation, followed by the outputs of WRF/CCSM, WRF/ECHAM and WRF/MIROC. The rationale for doing so is the same as that of the regional climate simulations: to test the performance of the true climate first and then that of the GCMs. The reasonably good results from the WRF model for the present-day climate over this region imply that they are suitable for use in the rainfall–runoff model. The daily scale precipitation and temperature derived from the RCMs were bi-linearly interpolated to the respective rainfall stations (Kon Plong, Kon Tum, Dak Doa) and meteorological station (Kon Tum). The SWAT model usually takes measured rainfall data from gauged stations as input,

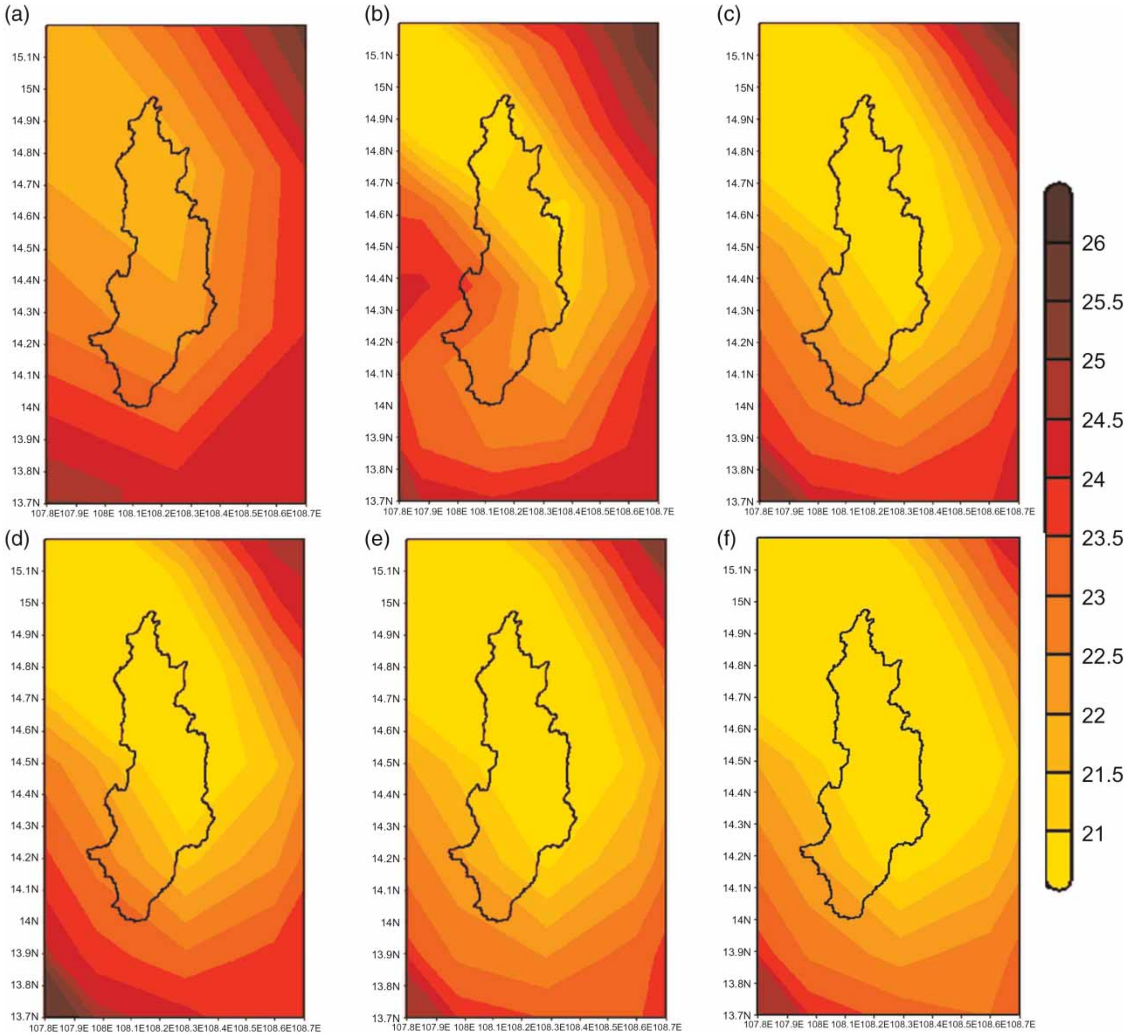

Figure 5 | Annual surface temperature over Dakbla during 1981–1990 (in °C): (a) CRU; (b) APH; (c) WRF/ERA; (d) WRF/CCSM; (e) WRF/ECHAM; and (f) WRF/MIROC.

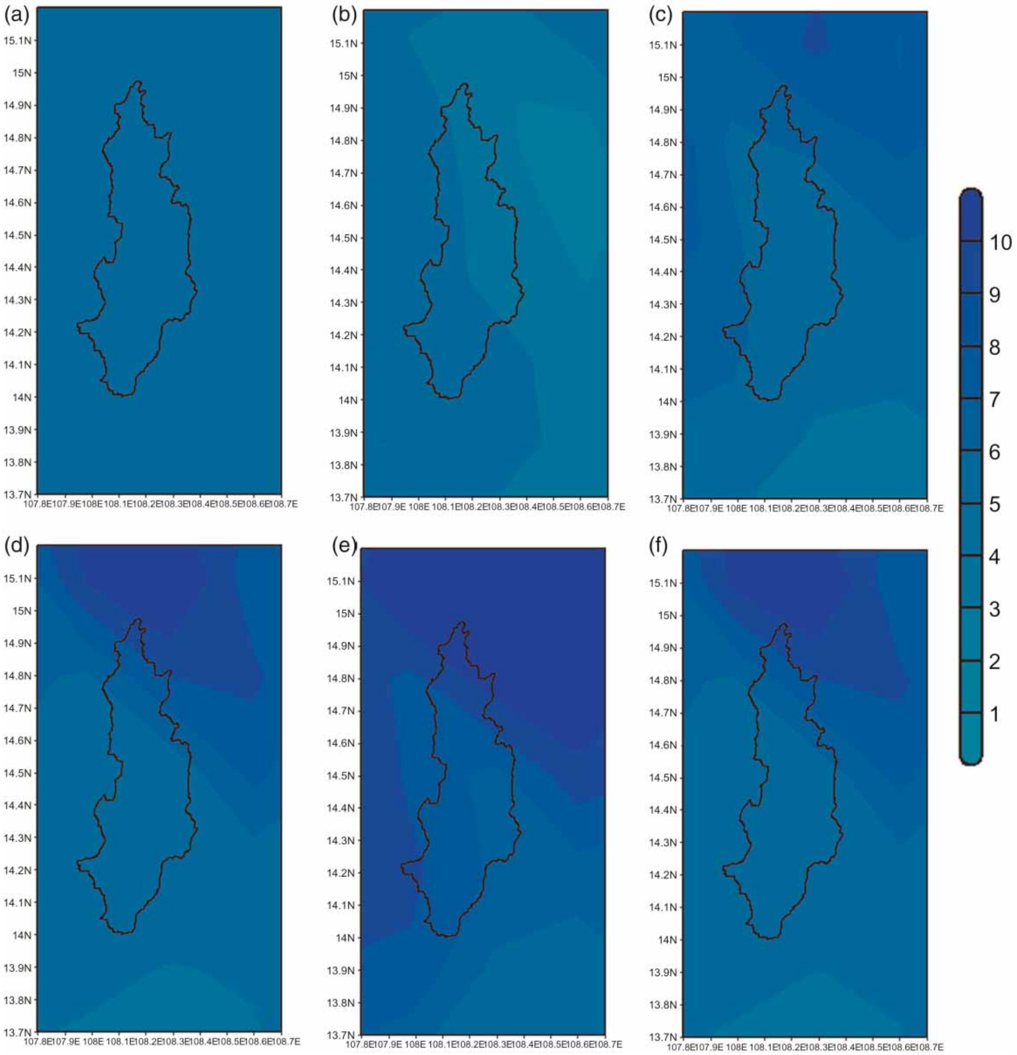

Figure 6 | Annual daily precipitation over Dakbla during 1981–1990 (in mm day^{-1}): (a) CRU; (b) APH; (c) WRF/ERA; (d) WRF/CCSM; (e) WRF/ECHAM; and (f) WRF/MIROC.

then distributes its values to all of its sub-catchments. An interpolation is therefore required to compute the station data (at a particular grid point) when using gridded data. Linear interpolation is therefore applied in this case. The bilinear interpolation method is an extension of the linear interpolation for interpolating functions of two variables on a regular grid; this is therefore used to extract precipitation value from station data at a grid point, from the entire gridded data source derived from the RCM output. The same approach is applied for the surface temperature.

Before the future stream flow results are discussed, it is also helpful to assess the future changes in the mean surface temperature and precipitation over the Dakbla region. Figure 7 displays the future response of the delta change in annual scale for Dakbla region over scenario A2 for three different models: (a) WRF/CCSM; (b) WRF/ECHAM; and (c) WRF/MIROC for surface temperature and precipitation. It can be seen that WRF/CCSM projects the least surface temperature increase compared to WRF/ECHAM and WRF/MIROC. The change in temperature from these three model scenarios ranges between 2.6 and 3.7 °C. Precipitation is also expected to increase annually by 20–50%, with the largest (smallest) changes simulated by WRF/MIROC (WRF/CCSM).

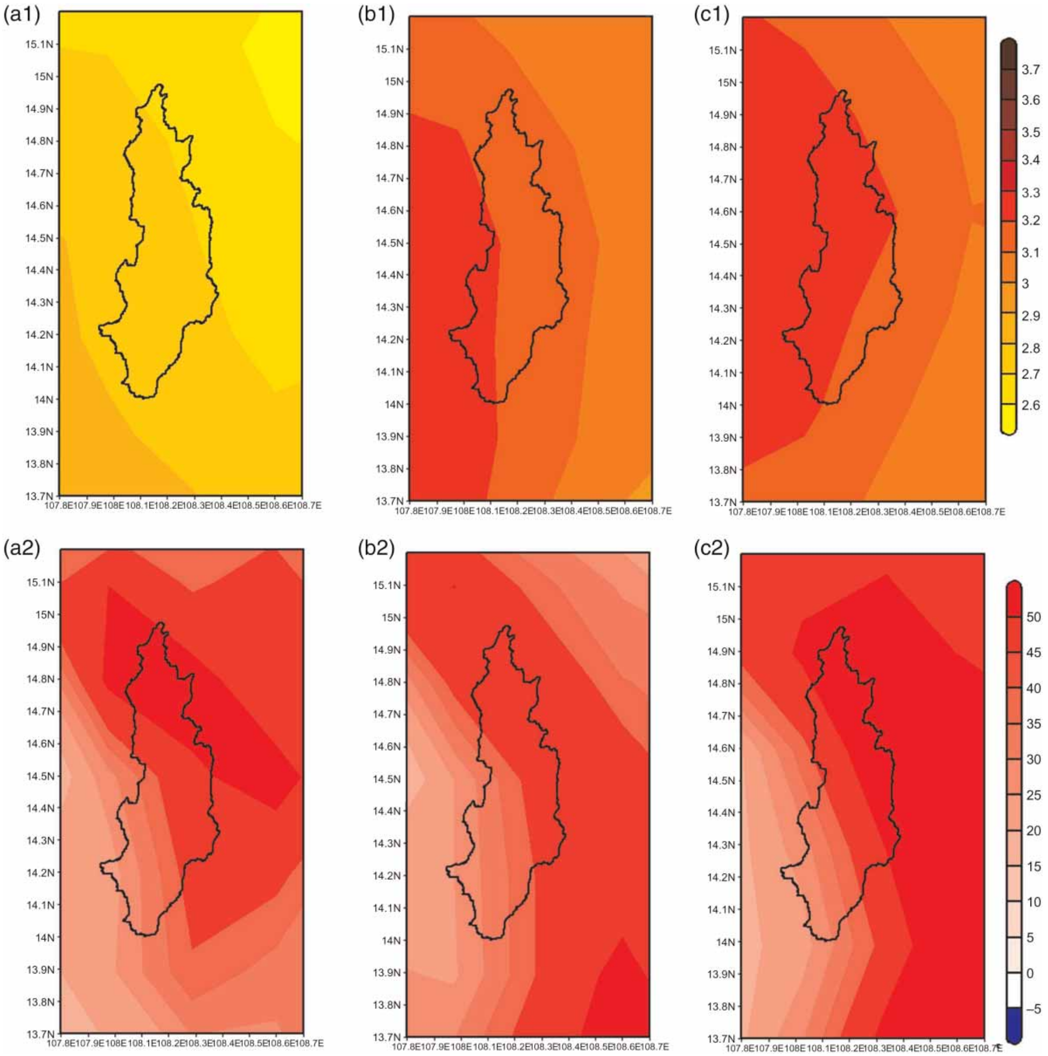

Figure 7 | Future response of (1) surface temperature and (2) daily precipitation over Dakbla: (a) WRF/CCSM; (b) WRF/ECHAM; and (c) WRF/MIROC.

Figure 8 shows the stream flow simulated by the SWAT model for the baseline (1981–1990) (black) and future (2091–2100) (red; see colour version online) period derived from the inputs (precipitation, temperature) from the three different RCM integrations – WRF/CCSM, WRF/ECHAM and WRF/MIROC – all using the same A2 scenario.

It can be seen that, over an annual scale, the stream flow simulated by WRF/CCSM A2 scenario shows an increase of 38% in the future, WRF/ECHAM A2 indicates an increase of 37% and WRF/MIROC shows the highest increase of 46%. The low flow period during the dry season NDJFMA also indicates a slight increase from all datasets. This finding is important because drought is one of the severe threats to this Central Highland region of Vietnam and has strong implications due to the high potential for hydropower.

In order to assess the characteristics of extreme rainfall and stream flow time series, a boxplot graph is shown in Figure 9 for both rainfall and discharge at the Kon Tum station. Overall, the WRF/ECHAM results indicate more rainfall compared to the other two RCM integrations, suggesting higher stream flow data. The maximum value of such a discharge is seen in the future stream flow for the WRF/ECHAM driven simulation, at 600 $m^3 s^{-1}$.

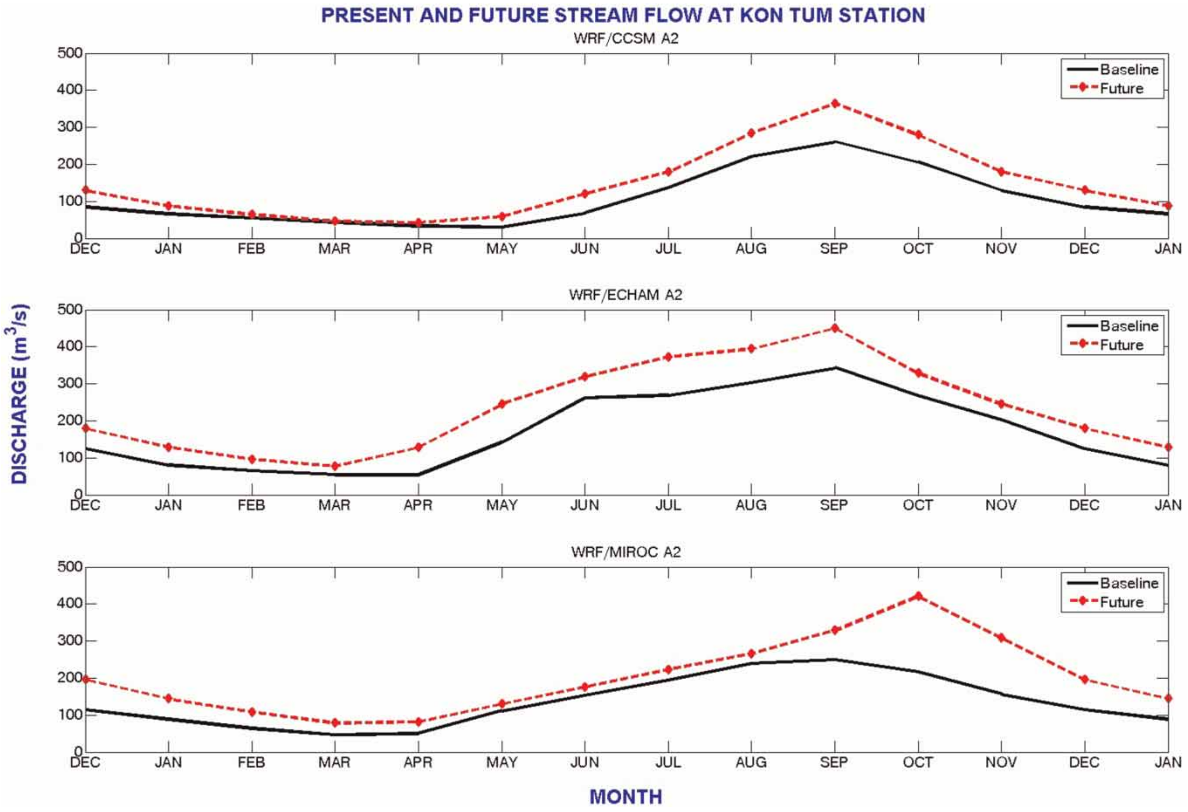

Figure 8 | Baseline and future stream flow at Kon Tum station for three RCMs.

On a daily scale study of extremes, the probability distribution function compares the rainfall and stream flow for the three different RCM results for the baseline and future periods (Figure 10). All three RCM results agree that future stream flow has higher frequency distribution for high discharge ($>100\,\mathrm{m^3\,s^{-1}}$) compared to the baseline. For the extreme case, a discharge value of more than $480\,\mathrm{m^3\,s^{-1}}$ indicates a higher frequency of future stream flow. This must be taken very seriously, as very high discharge is critical for river operation management.

CONCLUSIONS

In this study, regional climate model outputs of precipitation and surface temperature were applied to a hydrological model (SWAT), calibrated using the ParaSol method, and its simulated discharges were compared to their observed counterparts. The performance of the model using station data rainfall has been found satisfactory; the model-derived rainfall was therefore also used to assess stream flow simulation over the current and future climate. Using the RCM outputs, the present-day and future stream flows were also simulated. Results show that the future stream flow over the Dakbla river basin is expected to increase, especially during the rainy season, which has implications not only for flood mitigation measures but also for water resources management, hydropower and agriculture. Extreme values of rainfall and discharges indicate that necessary steps should be taken for appropriate river operation management.

However, much more work is required to improve confidence in these results. Further higher resolution simulation (5–10 km) of the RCMs may be required to obtain more credible estimates of present-day and future precipitation. Since this result has been obtained only from a few RCM simulations of future climates, it is recommended to obtain an ensemble estimate of future climate change by downscaling

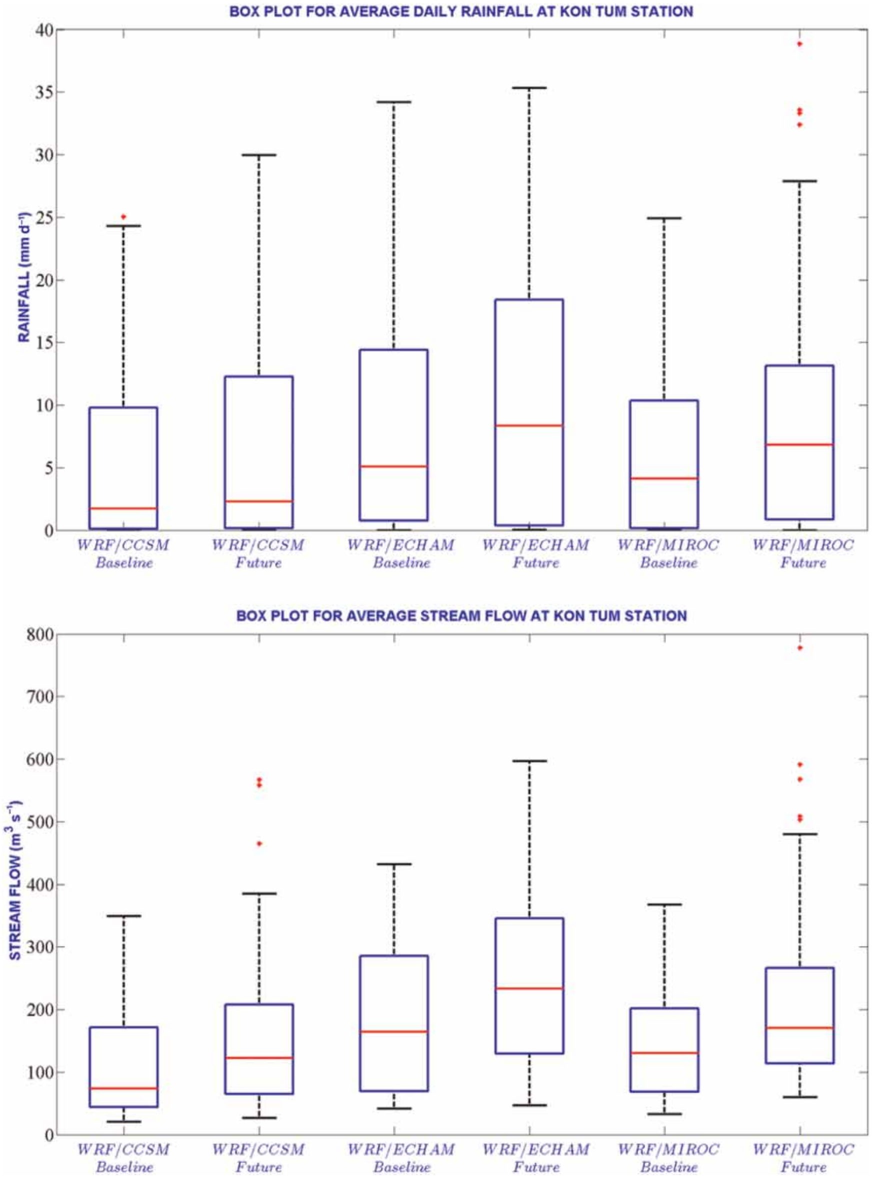

Figure 9 | Box plot for baseline and future for three RCMs at Kon Tum station, top: precipitation and bottom: stream flow.

more GCMs or by using perturbed initial conditions to the RCM to derive multiple estimates of climate. The hydrological simulations using the results of the derived ensemble climate simulations will add to the confidence of such a hydrological impact study.

Further developments in the RCM model physics and dynamics might also yield improvements in the climate simulations, yielding a better quality of RCM outputs which in turn might improve the hydrological simulations. As to some uncertainties from the hydrological model, improved spatial data such as the DEM might help to improve the stream flow simulations since the current version was mapped a few years ago in 2005. Other than the ParaSol method which was used for calibration, a few other auto-calibration methods which are coupled to SWAT-CUP model (SWAT Calibration Uncertainty Procedures, Abbaspour *et al.* 2007) might yield more possible outcomes which could help to understand a wider range of uncertainties.

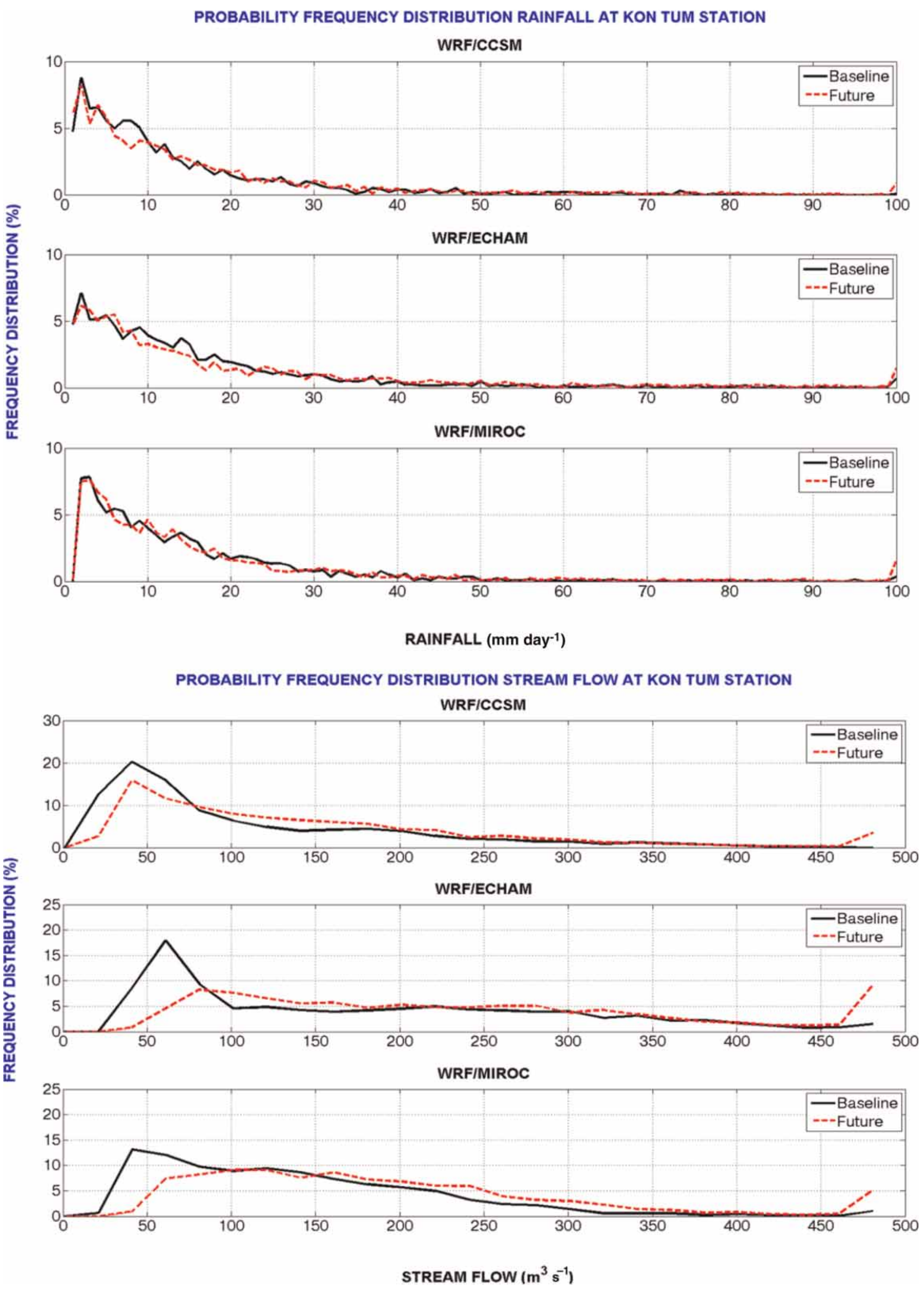

Figure 10 | Probability distribution function for baseline and future for three RCMs at Kon Tum station, top: precipitation and bottom: stream flow.

However, the applications of these methods are comprehensive exercises that entail more sensitivity studies and experimentations; they are as such beyond the scope of this paper, yet provide possible future research work. The research findings from this study are still useful as they yield some 'new' information that might yield clues to the wider and larger changes to come. This study is one of the first detailed RCM studies undertaken over this region to provide preliminary possible future climate change information to policy makers. As these several uncertainties will be constrained down the road once improvements in the modelling are achieved, those plausible wider and larger changes could be used for further assessments of future changes.

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