Simulation of Future Daily Rainfall Scenario using Stochastic Rainfall Generator for a Rice-Growing Irrigation Scheme in Malaysia

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ABSTRACT—*Rainfall is an important component in paddy water demand model for determining daily irrigation requirements. Knowledge of how it is likely to evolve in future is therefore indispensable for paddy farming. This paper presents a quantitative assessment of the possible changes in future rainfall performed by downscaling GCM simulations for the Tanjung Karang irrigation scheme in Malaysia. The stochastic rainfall generator model (WGEN), never applied in Malaysia before, was adopted for downscaling and simulation of future daily rainfall using 16 simulations developed from 10 GCMs driven by the latest Representative Concentration Pathways scenarios (RCPs), 6.0 and 8.5 for two future periods (2030s and 2060s). Change factors were computed from the GCMs using the delta change method which were used in perturbing model parameters for future simulationof rainfall. The results obtained show a wide spread among GCMs, although they all agree in the direction of future rainfall changes. Overall annual rainfall is predicted to increase by 6% and 14% for dry and wet seasons, respectively under RCP6.0 and 8.5 scenarios. Additionally, seasonal effective rainfall projections show a decreasing change of 5% during dry season under RCP6.0, while an increase change of 8 to 13%is predicted in wet season from moderate (RCP6.0) to the most severe (RCP8.5) scenarios respectively. This is an area of concern that farmers and water managers may need to keep alert so as to secure future paddy irrigation water. Theprojected changes in rainfall regimerequire further work before concluding whether these changes have negative or positive consequences for the paddy sector. The stochastic model will be adopted as a component in a future study aimed at developing a water management-support tool for modeling water allocations and irrigation schedules in paddy fields.*

Keywords—Daily rainfall,Rainfall generator, Irrigation demand, GCMs, Paddy

1. INTRODUCTION

Rainfall is an important component in rice production that drives both upland (rain-fed) and lowland (irrigated) rice cultivation and also plays a significant role in the design of irrigation systems and fixing paddy water requirements. The Asia region is largest rice producer producing about 94% of the total world production [1] and consuming more than 90% of total irrigation water drawn from river basins [2]. Global demand for rice consumption is projected to increase by 35% by 2030 due to expanding population [2]. However, climate change is a real and yet complex challenge in terms of future rainfall availability and reliability for the farming sector. Global changes in rainfall frequencies, patterns and magnitudes associated with the changes in climate have been reported across the globe[3, 4] which places severe strain on agricultural water supplies. Thus, the combined effects of increased demand for rice food and climate change pushes agricultural production to the edge of sustainability.

In Malaysia, the paddy farming sector is small in terms of its contribution to national gross domestic product, and yet remains significant with respect to food production, rural employment and livelihoods in the country. Rice being a staple food for the country is produced largely under irrigation infrastructure to ensure continuous production. A total irrigable land in excess of 394,000 hectares is confined under 8 large granary schemes designated as 'the hub' for rice production for sustaining the nation's self-sufficiency level. Rice production in these areas is during the wet season and the dry. The natural pattern is characterized by poor distribution and small amounts of rainfall[2]. More than 51% of the paddy water requirements are by and large satisfied by natural rainfall in these massive irrigation schemes, with the wet season practicing supplemental irrigation while full irrigation is practiced during the dry season. Consequently, the irrigation systems design criteria is not based on full supply, since a significant portion of the irrigation water is anticipated to be contributed by rain water[5]. Although Malaysia is endowed with rainfall throughout the year, there is growing concern about water availability for future paddy cultivation in this country, considering the increasing pressure that climate change will place on paddy cultivation. It is not yet clear how rainfall patterns are changing and how the changes will affect paddy irrigation requirements. Current quantitative studies related on this topic are still scarce in Malaysia, and moreover, the country's climate change policy is still being developed. To recognize the role of rainfall in paddy farming, it is therefore an emerging requirement to understand the impact of climate change on this parameter.

One step towards evaluating this challenge is through development of future rainfall scenarios using up-to-date climate tools, and is therefore the focus of this study. Global climate models (GCMs) are the appropriate tools currently employed in providing climate projections of both present-day and distant future climate variables. However, these models are not tailored to operate on small local-scales[6, 7],their current resolution is too large for direct use in local scale impact studies. As such, GCM outputs often go through downscaling to adjust their information to be more realistic with local scale scenarios. Several downscaling techniques have evolved in the passage of time derived from two categories: dynamic and statistical downscaling. Dynamic technique, often viewed as a miniature global climate model attempts to model local variables by increasing their resolutions by reducing the horizontal spacing (typically around 25x25 km or smaller). Although they are efficient in producing climate data, they have not gained popularity because they tend to use complex processes and approaches [8]in order to capture local-scale variations. Statistical methods such as 1) regression-based procedures, 2) weather typing, and 3) stochastic weather generators[6, 9] are most commonly used in climate studies because they are cheap to apply and provide site-specific climate information[10]. The choice of methods depends largely on study focus and required time scale of data. Details on the theories behind these techniques and guidelines on their choice for a particular purpose may be found in the work of[11-14].

Weather generators are stochastic models for generating climate variables such as rainfall and temperature for local-scale application by using historical data series as baseline[15]. Due to their stochastic nature, they are increasingly being used in several water resource related applications such as in agriculture to produce long daily synthetic climate data as input for modeling of crop yields[16, 17]. Weather generators have also be modified for downscaling GCM-generated outputs for climate change related studies[18] and are relatively cheap and easy to handle which is probably why they have received great attention in many studies. Two common types of weather generator models have evolved over the years: the parametric-models, as represented by the Richardson weather generator (WGEN) which is based on the Markov chain dependent for simulating rainfall occurrence and distribution function for simulating rainfall amounts[13, 18-20]. The semi- parametric models on the other hand, is the one developed by[21] which applies semi-empirical distributions to simulate rainfall processes. Although both approaches are good, their main limitation is that they are site-specific and so they cannot directly be used prior to calibration and verification using local climate data. Details for further review on their history and previous applications can be found from[22].

In Malaysia, previous commendable research on rainfall has been done using historical data focusing on a range of issues such as, rainfall spatial trends[23], assessing extreme rainfall events[24], characterizing rainfall using drought indices[25], and spatial distribution of wet and dry spells[26]. To date, with the increasing strain in water demand it is still a challenge to obtain climate data series based on future climate projections for paddy irrigation planning. The only available study was carried out by the National Hydraulic Research institute of Malaysia [27]where they evaluated 3 GCMs in simulating future climate over the country downscaled using PRECIS regional climate model at 25 x 25 km resolution. Their study provided good preliminary climate scenarios for the country from which subsequent further detailed studies could be referenced. However, their study was based on the earlier greenhouse gas emission scenarios (consisting of A1, A2, B1, B2) from the Special Report on Emission Scenario in the IPCC AR4. These scenarios have recently been substituted by the newly released set of scenarios called *Representative Concentration Pathways* (RCPs), consisting of RCP 2.6, 4.5, 6.0 and 8.5, which are now based on the approximate range of plausible radiative forcing (Wm^{-2}) scenarios by end of the current century. Radiative forcing is that extra heat which the lower part of the atmosphere will retain as a result of additional greenhouse gases[28].

Currently, no studies on simulation of future rainfall have been performed in any of Malaysia's rice growing using stochastic rainfall generator downscaling model. Further, no previous studies have used the updated RCP emission scenarios that are currently the most credible scenarios and are consistent with the time. The inspiration then is to attempt to fill this research gap. In the current study, future daily rainfall scenario over Tanjung Karang Irrigation Scheme is simulated with a stochastic rainfall generator model using an ensemble of 10 GCMs under the most up-to-date RCP emission scenarios for the control period as represented by 1976-2005 and two future periods 2010-2039 (2030s), and 2040-2069 (2050s). The outcomes of this study will be (1) used to develop future paddy cropping schedules that are consistent with future obtaining rain scenarios, and, (2) the stochastic rainfall model will be used as a component in a subsequent study of developing a new water management-support tool for modeling water allocation and irrigation schedules in paddy fields. A brief description of the methodology in given in Section 2 of this paper which include the study area, model training and testing, and model application for downscaling future rainfall. The results and analysis are provided in Section 3, which include model evaluation, future rainfall scenario. Finally, summary and conclusion of the study is given in Section 4.

2. METHODOLOGY

2.1 Study Area

Tanjung Karang Irrigation Scheme (TAKRIS) has been chosen as a study area among the 8 large-scale rice growing irrigation schemes shown in Figure 1(a). The scheme is situated in the District of Kuala Selangor in Selangor State on a flat coastal plain and lies within 3.4°E and 100.59°N. The scheme's irrigation system configuration is also shown in figure 1(b). A total gross irrigable area of 20,000 hectares of paddy land is occupied and is the 4^{th} largest rice scheme in the country. About 123 irrigation blocks are supplied with irrigation water from the runoff of the Upper Bernam river basin which is diverted and conveyed via a 15 km long Feeder canal and pumped into the scheme tertiary canal systems through the main canal.

The area receives an annual rainfall of about 1,700 mm $year^{-1}$ and experiences a tropical climate with marked differences between the two cropping seasons: wet and dry. The dry season runs from February to July, and is characterized by dry spells that occurs during the southwest monsoon season. The wet season coincides with the northeast monsoon which starts around August to January and is usually associated with heavy and sometimes destructive rains. The scheme practices double cropping rice production system, with the first cropping starting from February to July during the dry season while the second cropping is during the wet season which occurs between August to January. Cases of water rationing are common during dry season which has led to frequent water shortages for paddy fields in the past. The river discharge records are generally low during the same period. Therefore, knowledge of future rainfall is indispensable for this scheme in order to minimize its proneness to frequent drought conditions.

2.2 Model Description

The rainfall generator model used in this study is the modified version of Weather Generator (WGEN) developed by[19]to generate long series of daily rainfall. The model simulates both rainfall occurrence and rainfall amounts separately. Rainfall occurrence is described by the Markov chain process where occurrence of rainfall depends on the state of the previous event. It should be mentioned at this point that, a two-state first-order Markov chain process for modeling rain d in this study. In this approach, rainfall is described as either it occurs or it does not occur (two-state) and that its occurrence fall was adopted is dependent on previous day (first-order). Although recent studies have modeled rainfall with more-states, (that is, heavy rain, moderate rain or no rain) and with higher-orders (that is, rainfall occurrence being dependent on several previous days), this study adopts the former because it is suitable for the intended purpose of the study.

Figure 1 (a) Locations of large-scale rice irrigation schemes in Peninsular Malaysia; (b) Tanjung Karang Rice Irrigation Scheme (TAKRIS) at Northwest Selangor (Source: Rowshon et al., 2013)

With the first-order Markov chain model, rainfall occurrence is described by two transitional probabilities, $P_{(dw)}$ the probability of a wet day preceded by a dry day and $P_{[30]}$the probability of a wet day preceded by another wet day, expressed by equation 1 and 2. The 2 transitional probabilities are computed from observed rainfall series and are constant for a given month but vary between the different months.

$$P_{dw} = P\{wet\ on\ day\ t \mid dry\ on\ day\ t-1\} \quad (1)$$
$$P_{ww} = P\{wet\ on\ day\ t \mid wet\ on\ day\ t-1\} \quad (2)$$

To simulate rainfall occurrence $P_s(t)$ on day t, a random number $U_t$is generated using MATLAB program and is compared with the critical transition probability (equation 4) which depends on rainfall state of the previous day t-*1* where wet day = *w* and dry day = *d*.

$$P_c = \begin{cases} P_{dw}\ if\ P_s(t-1) = d \\ P_{ww}\ if\ P_s(t-1) = w \end{cases} \quad (3)$$

A wet day is simulated when the random number is less than the critical probability, otherwise it is simulated as a dry day (equation 4).

$$P_s(t) = \begin{cases} w\ if\ U_t \le P_c \\ d\ if\ U_t > P_c \end{cases} \quad (4)$$

Variation of rainfall quantities is characterized using the probability density function that best describes rainfall amount *x*. Several distributions are widely used for rainfall amounts including the one parameter exponential which was used previously by[31] and [32]in their studies of rainfall in the Johor State in Peninsula Malaysia. Gamma distribution in equation 5 is adopted in this study mainly because it is the most popular choice in rainfall studies, whereas the former has been used comparatively rarely. The gamma distribution is fitted to all days modeled as wet days with a threshold of 1 mm as suggested in previous study in Malaysia[24].

$$f(x) = \frac{\left(x/_{\beta}\right)^{\alpha-1} exp\left(-x/_{\beta}\right)}{\beta\Gamma(\alpha)}; \alpha, \beta > 0; x > 0 \tag{5}$$

Where, $\Gamma(\alpha)$ represents the gamma function, α and β are shape and scale parameters computed using the maximum likelihood estimators[33]. As with the rainfall occurrence process, separate pairs of parameters defining rainfall amount are defined for a given month and vary from month to month such that rainfall simulation in the model algorithm is characterized by 4 parameters ($P_{(dw)}$, $P_{[30]}$, α and β) for each month.

2.3 Input data and model evaluation

Before applying the model for downscaling and future simulation, its performance in simulating rainfall series at the study area is evaluated. Its limitation is that it is a site-specific model whose parameters must be estimated from local climate using long series of historical data for each site. It cannot be applied directly in other climates without testing. Therefore calibration and verification is required at every station. In this study, 30 years of observed daily rainfall data from 1976-2005 collected from 5 stations distributed within the 40 km length of the scheme were obtained from the Irrigation Department in Malaysia. Out of these only 3 stations shown in Table 1 have good quality data with missing values of less than 15% for the study period and were used in model training and testing. Missing values of rainfall data were estimated using values from neighboring stations for the corresponding period of missing values.

Table 1 List of rainfall stations for the study area

Station	Latitude	Longitude	% missing values
3610014	03° 37’ 16’’	101° 02’ 28’’	12.6
3609012	03° 40’ 54’’	100° 59’ 31’’	4.4
3710006	03° 43’ 43’’	100° 04’ 59’’	9.8

The data was provided in the model to compute area specific parameters from the generated daily series by running the model 100 times. Generated rainfall statistics describing rainfall occurrence, quantity and distribution (including daily and monthly mean rainfall, standard deviation, rainy days, wet and dry spells and annual maximum rainfall) were computed from all 3 stations and compared against those produced from the model. Selected statistics are also similar with other previous studies in different locations[34, 35]. The 3 rainfall stations showed consistent changes during model testing. The results obtained from these comparisons are quite acceptable giving reasonable confidence about the performance and future outputs from the model. However, for future projections we have used only one station (that is, station no. 3609012) because of its spatial representativeness of the site.

2.4 Model application in downscaling future rainfall

The model described above is applied for downscaling of GCM outputs and simulation of future rainfall scenario over the Tanjung Karang rice irrigation scheme in the Selangor State. To do this, we employ the concept of change factors derived from GCM data for two sets of periods based on selected emission scenarios. Change factors can be considered as a simple and effective technique in relating GCM-scale projections with station observed variables. They have been applied in earlier rainfall downscaling studies[14, 36] and have also been used to other hydro-meteorological variables of interest[37]. The weakness of this approach however, is its reliance on the assumption of self-similarity theory which believes that the bias between current and future modeled climate will remain unchanged in future. This assumption is however, generally accepted in climate change studies as a necessary compromise to enable the use of GCM modeled information at local scale[34, 38].

2.5 Perturbing rainfall generator parameters

To incorporate the change in climate in the model, change factors were computed using GCM-simulated output by comparing the rainfall statistical parameters for the control period with those for the future periods. The term change factors express the difference between statistical parameters for these two periods. The two general approaches adopted in using change factors for downscaling rainfall[38], are expressed by equation 6 and 7.

1) Product factor: is generally used when the ratio between statistical parameters for future and control period is computed,

$$\frac{R^{FUT}}{R^{OBS}} = \frac{R^{GCM.FUT}}{R^{GCM.CTS}} \quad (6)$$

2) Delta change (or additive factor): is applied when the difference between statistical parameters for future and control period is calculated.

$$R^{GCM.FUT} - R^{GCM.CTS} = R^{FUT} - R^{OBS} \quad (7)$$

where*R* refers to rainfall statistical property, *OBS* and *FUT* represent observed and future scenarios respectively, *GCM.FUT* and *GCM.CTS* denote GCM model generated for future and control scenarios. In this study, the delta change method is used for perturbing the model parameters for simulation of future daily rainfall series. The procedure followed in applying change factors is presented in Figure 2.

2.6 GCM data extraction

Ten GCMs covering the whole globe were obtained from Program for Climate Model Diagnosis and Inter-comparison (PCMDI) website http://pcmdi3.llnl.gov/esgcet/home.htm and are presented in Table 2. The GCM outputs were extracted for the control period (1976-2005) as well as for future run (2010-2039 and 2040-2069). A single model projection represents a single picture of how the future is likely to unfold and is unlikely to give realistic results. As such, multiple models were selected to address GCM model uncertainties as it has been repeatedly demonstrated that a single model does not provide useful information in assessing impacts due to climate change[9, 39]. The recently updated emission scenarios called Representative Concentration Pathways (RCPs) were selected for application in this study. The RCP 6.0 and 8.5 scenarios were chosen considering that Malaysia is one of the fast developing countries in Southeast Asia region. RCP6.0 is a medium scenario which attempts to stabilize total radiative forcing by end of 2100 by considering developed technologies and strategies for reducing greenhouse gases (GHGs) emissions. The RCP8.5 is a high emission scenario representing little effort in reducing GHGs by end of the21stcentury.

Here, daily precipitation flux is used as a predictor of future rainfall because it can represent well the changes in rainfall associated with synoptic-scale circulation changes and is simulated well by most climate models[40, 41]. Precipitation flux data from 1976 to 2069 was extracted from a single grid cell covering the irrigation scheme area and downscaled using the change factor method in the rainfall generator model as previously explained.

Table 2 List of Climate Models used and their corresponding RCP emission scenarios

GCM	**Organization**	**Scenario used**	**Atmospheric Resolution**	
			Lat	Lon.
CanESM2	Canadian Centre for Climate Modelling and Analysis	RCP8.5	2.8	2.8
CCSM4	National Center for Atmospheric Research	RCP6.0, RCP8.5	1.25	0.94
CNRM-CM5	Centre National de RecherchesMétéorologiques / Centre Européen de Recherche et Formation Avancée en CalculScientifique	RCP8.5	1.4	1.4
CSIRO	Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence	RCP6.0, RCP8.5	1.8	1.8
GFDL-ESM2G	NOAA Geophysical Fluid Dynamics Laboratory	RCP6.0, RCP8.5	2.5	2.0

GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory	RCP6.0, RCP8.5	2.5	2.0
HadGEM2-CC	Met Office Hadley Centre	RCP8.5	1.88	1.25
HadGEM2-ES	Met Office Hadley Centre	RCP 6.0, RCP 8.5	1.88	1.25
MPI-ESM-LR	Max-Planck-InstitutfürMeteorologie (Max Planck Institute for Meteorology)	RCP 8.5	1.88	1.87
MRI-CGCM3	Meteorological Research Institute	RCP6.0, RCP8.5	1.1	1.1

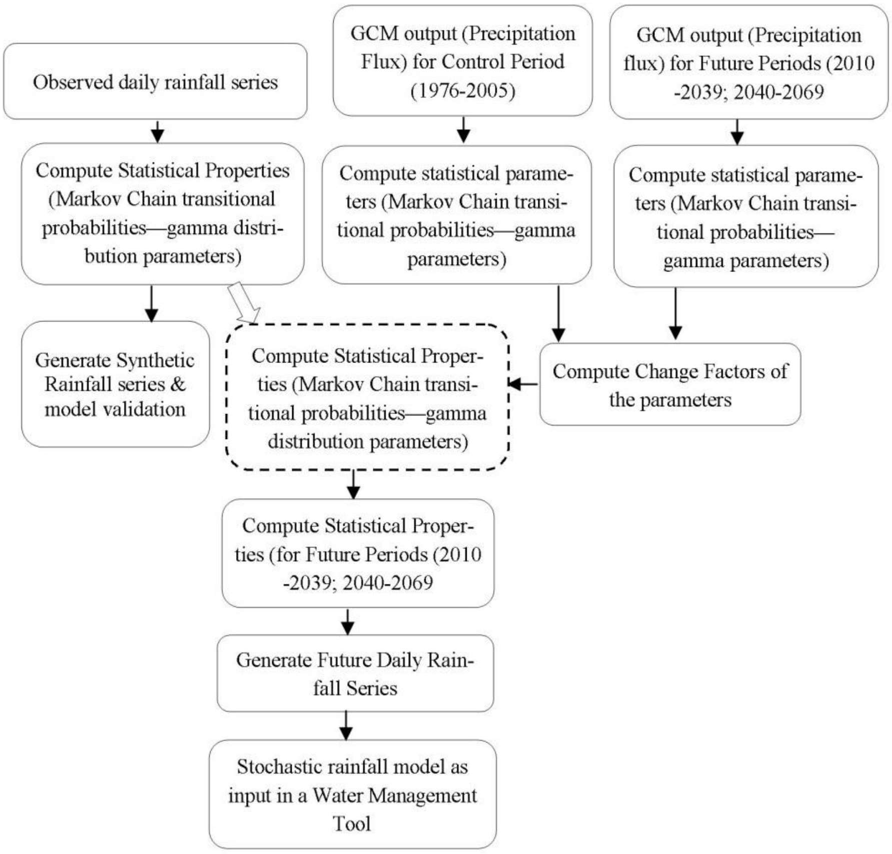


Figure 2 Flowchart illustrated downscaling technique of rainfall with stochastic weather generator

2.7 Modeling future seasonal effective rainfall

Rainfall is an important parameter in the paddy water demand model for determining daily water requirement (equation 8). Thus a good estimate of future seasonal effective rainfall is required to maximize the use of rainfall and save river water for future use. Effective rainfall can be defined simply as a proportion of total received rainfall which is usable directly in the paddy field, after losses from runoff and deep percolation[42].

$$SW_j = SW_{j-1} + IR_j + RF_j - ET_j - SP_j - DR_j \qquad (8)$$

Where, SW_j is ponding water depth in the paddy field (mm), IR_j is irrigation water supplied during the period (mm), RF_j is rainfall (mm), ET_j is crop evapotranspiration during the period (mm), SP_j is seepage during the period (mm), DR_j is drainage in the paddy field outlet (mm). To determine effective rainfall in paddy fields can be tedious. In this study, weekly effective rainfall (ERF_j) is based on averaged future projected rainfall using the empirical formula (equation 9) developed for Tanjung Karang Scheme[2, 43]. The impact of climate change on future rainfall was then evaluated based on changes in rainfall indices against the control scenario. Results are presented in the next section in tables and figures.

$$EFR_j = \begin{cases} 0.6RF \ if \ RF < 50 \ mm \\ 0.3(RF - 50) + 30 \ if \ RF > 50 \ mm \end{cases} \qquad (9)$$

3. RESULTS AND DISCUSSION

3.1 Model performance

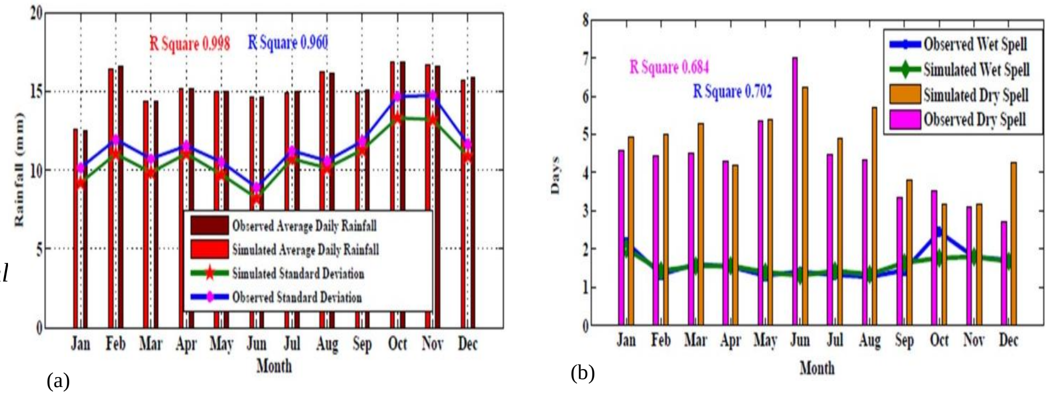
Estimated transition probabilities and gamma parameters derived from the observed data indicates that during the off (dry) season the probability of not receiving rains is high if there was also no rain the previous day, and the chance of receiving rains when it was raining the previous day starts to increase during the main (wet) rice growing season. Computed transitional probabilities and gamma parameters for observed period from 1976-2005 is shown in Table 3.

Figure 3(a) presents simulated rainfall and standard deviation for the observed period. The results compare well with observed rainfall in the area. As it can be observed, the daily mean rainfall from month to month is accurately duplicated by the model with R-squared value of 0.99. With regards to standard deviation, the model shows good performance skill, although there is a slight underestimate throughout all the months. The month of October and November were more underestimated compared to the other months, but overall it gives acceptable results with R-squared value of 0.96. It is however, generally acknowledged that downscaling models are often poor in modeling rainfall variance accurately [13]. The results show close resemblance with the rainfall pattern in Malaysia where most of the rain fall during the northeast monsoon season which coincides with the main (wet) season in the irrigation sector. Lower rainfall is in the dry season (commonly referred to as off-season) which occurs during the southwest monsoon season accompanied by low river flows.

Figure 3(b) shows model results of simulated wet and dry spell lengths. The duration of wet and dry spell series was reasonably simulated for Tanjung Karang site with R-squared values of 0.68 and 0.70 respectively. The model failed to simulate the peak wet spell of October and that of January month. However, the pattern of wet spell during both seasons was reproduced more precisely for almost all months than the wet spell values. The model showed that higher wetter days occur during the main cropping season (August through to December sometimes overlapping to January), and that the dry cropping season (February to July) is often occupied by less wet days. Similarly, results of simulated dry spell length follow a similar trend. The model consistently overestimated dry spell length throughout both seasons except in April and May. However, it underestimated slightly the month (June) which has the highest dry spell length. The model has shown skill in simulating the pattern of dry spell length during both seasons. As can be expected, there are fewer dry days during the main (wet) rice growing season characterized by the northeast monsoon rainfall and more dry days are experienced during the off-season rice growing period. From the evaluation results, it is apparent that the stochastic rainfall generator model has good skills in simulating rainfall statistical parameters which are similar to the observed daily rainfall, and for this reason it was used for downscaling of future rainfall with GCM outputs.

Table 3 Summary of estimated transition probabilities for different months for the observed period

January			February			March		
	Dry day	Rain day		Dry day	Rain day		Dry day	Rain day
Dry day	0.80	0.20	Dry day	0.80	0.20	Dry day	0.80	0.20
Rain day	0.45	0.55	Rain day	0.67	0.33	Rain day	0.60	0.40
April			May			June		
	Dry day	Rain day		Dry day	Rain day		Dry day	Rain day
Dry day	0.75	0.25	Dry day	0.81	0.19	Dry day	0.86	0.14
Rain day	0.62	0.38	Rain day	0.69	0.31	Rain day	0.75	0.25
July			August			September		
	Dry day	Rain day		Dry day	Rain day		Dry day	Rain day
Dry day	0.78	0.22	Dry day	0.82	0.18	Dry day	0.72	0.28
Rain day	0.66	0.34	Rain day	0.73	0.27	Rain day	0.58	0.42
October			November			December		
	Dry day	Rain day		Dry day	Rain day		Dry day	Rain day
Dry day	0.67	0.33	Dry day	0.67	0.33	Dry day	0.76	0.24
Rain day	0.54	0.46	Rain day	0.52	0.48	Rain day	0.57	0.43



(a) (b)

Figure 3 Comparison of rainfall statistics at station no.3609012: (a) mean daily rainfall and standard deviation, (b) wet and dry spell lengths

3.2 GCM projections of rainfall

Table 4 provides summary results on performance of the 10 GCMs in terms projected seasonal and annual rainfall under RCP 6.0 and 8.5 scenarios for future time periods (2010-2039 and 2040-2069). For dry season under moderate (RCP 6.0) emission scenario, all models (with the exception of GFDL-ESM2G and GFDL-ESM2M) predicted a decrease in total seasonal rainfall for future periods. The highest decreasing change (34%) was observed with HadGEM2-ES, although later in the 2060s a decrease of up to 17% is observed from the same GCM. Similarly, in the worst case scenario RCP8.5, the same GCMs projected a decrease in seasonal rainfall except GFDL-ESM2G, GFDL-ESM2M and HadGEM2-CC who predicted an increase. For wet (main) season, all models show an increase in seasonal rainfall under both emission scenarios for all future periods. In fact models HadGEM2-CC, CSIRO and MRI-CGCM3 showed the biggest rainfall increase of 61, 57 and 28% respectively. Only HadGEM2-ES maintained a decreasing change of 18% for 2060s period.

With respect to the multi-model mean, the dry season shows an average decrease of 5% in total rainfall under scenario RCP 6.0 for both periods while scenario RCP 8.5 is projected to have no significant change in future rainfall in dry season. However, during the wet (main) season, the multi-model mean shows a general increase of 9% and 15% for scenario RCP 6.0 and 8.5 respectively for the two future time periods. Overall, there is general increasing trend in annual rainfall of 3% and 10% for scenario RCP 6.0 and RCP 8.5 respectively in future. Overall percentage change in seasonal rainfall compared to the control period for both scenarios and both future periods is presented in Figure 4 in box-plots. Figure 5 shows the performance of each GCM in simulating the observed annual rainfall during the control period. The annual rainfall simulated by the GCMs are averaged and plotted as multi-model MEAN and each GCM is compared with the OBS value. It can be seen that each GCM exhibits large spread of the annual rainfall. These spreads underscore the inherent uncertainties in climate model predictions by GCMs. The analysis shows that the multi model mean did not actually give better representation as it is not matching well with the observed value. Only CanESM2 and MRI models are closest to the observed mean value. This could be attributed to using fewer models as compared to using as many models as possible. However, it is still safe to use the multi-model mean because a single or few GCM projections (CanESM2 and MRI in this case) are unlikely to represent the future possibilities of the impacts and is therefore unwise to rely on them[44].

Table 4 Change factors for seasonal rainfall for RCP6.0 and 8.5 and 2010-2039 and 2040-2069 period

GCMs	Dry Season (%)				Wet Season (%)				Annual (%)			
	2010-2039		2040-2069		2010-2039		2040-2069		2010-2039		2040-2069	
	RCP6.0	RCP8.5	RCP6.0	RCP8.5	RCP6.0	RCP8.5	RCP6.0	RCP8.5	RCP6.0	RCP8.5	RCP6.0	RCP8.5
CanESM2		-0.0		-11.3		10.1		9.2		5.8		0.6
CCSM4	-17.0	-9.6	-3.3	-0.0	-0.1	2.9	1.6	6.7	-7.1	-2.3	-0.3	3.9
CNRM		0.5		-8.5		0.9		-1.0		0.7		-4.1
CSIRO	-1.2	-0.4	-1.3	-17.5	43.2	57.7	50.4	12.8	24.7	33.6	29.0	0.2
GFDL-ESM2G	9.2	-5.0	15.5	18.9	3.5	-0.9	-0.3	12.9	5.9	-2.6	6.2	15.4
GFDL-ESM2M	5.8	9.7	10.9	-2.3	6.1	16.3	14.8	9.2	6.0	13.6	13.2	4.4
HadGEM2-CC		39.0		42.6		61.0		52.6		51.9		48.4
HadGEM2-ES	-21.0	-18.6	-34.5	-17.3	2.8	6.1	-18.1	0.5	-7.0	-4.1	-24.9	-6.8
MPI-ESM-LR		14.4		-0.1		11.1		16.2		12.5		9.4
MRI-CGCM3	-4.2	-8.7	-14.9	6.5	2.6	2.3	3.7	28.2	-0.1	-2.2	-3.9	19.2
Multi-Model Mean	-4.7	2.1	-4.6	1.0	9.7	16.7	8.7	14.7	3.7	10.7	3.1	9.0

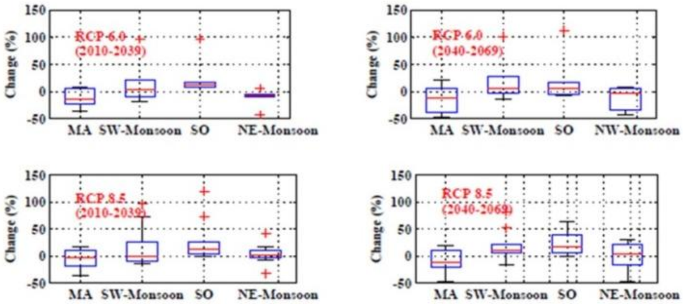


Figure 4 Changes in seasonal rainfall using 10 GCMs projections for future period, for a) RCP6.0 scenario (2010-2039) - top left. b) RCP6.0 scenario (2040-2069) - top right. c) RCP8.5 scenario (2010-2039) - bottom left. d) RCP8.5 scenario (2040-2069) - bottom right

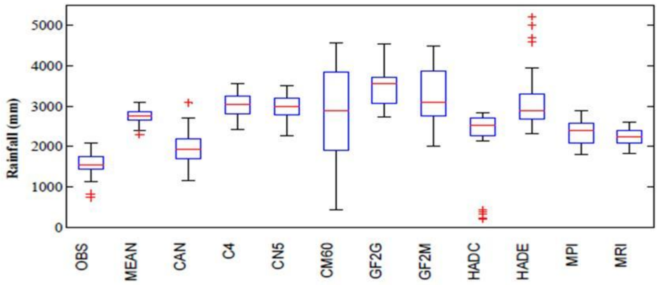


Figure 5 A comparison of annual rainfall between observed (OBS) period (1976-2005) and future period as simulated by each GCM as well as average of all GCM values denoted MEAN

3.3 Impact on future rainfall scenarios

Projected annual rainfall patterns

Table 5 presents a summary of projected changes in rainfall parameters corresponding to the climate scenarios downscaled for the study area. Figure 6(a) displays the ensemble changes in annual rainfall at station no 3609012 for the 2030s and 2060s time periods projected under two RCP scenarios and compared to the control period (1976-2005). The annual rainfall for the area is projected to increase under both scenarios RCP6.0 and 8.5 at station no3609012. Under RCP 6.0 scenario, the average rainfall increases by 6% (1601 mm) and 7% (1621 mm) for 2030s and 2060s respective future periods against the long-term average of 1515 mm for the control period. The greatest increase is 14% (1721 mm) occurring during both 2030s and 2060s under the most severe scenario (RCP 8.5) at the same station. Figure 6(b) shows that the decrease is in dry season while the highest increase is during the wet season. The results obtained are similar to the preliminary study by[27] on downscaling using PRECIS Regional model where they reported that the country is projected to experience drier periods from January to April especially the northern region. Similarly, two other recent streamflow studies reported similar increase in rainfall by end of the century but lesser rainfall in the early years[45, 46].

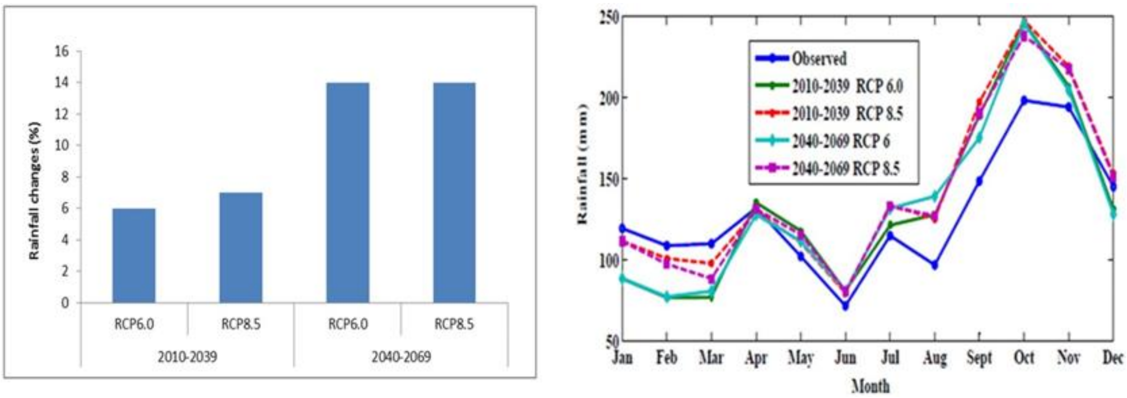


Figure 6 Changes of rainfall (a) in % for the 2030s and 2060s under RCP6.0 and 8.5, and (b) comparison of mean monthly rainfall for control and future periods at station no3609012

Effects on effective seasonal rainfall

Seasonal effective rainfall changes during the two rice growing seasons under the two scenarios for the periods of 2030s and 2060s against the control period are explained by Table 5 and Figure 7. At the station, the dry season effective rainfall is projected to decrease by 5% (365 mm) for scenario RCP6.0 for both future periods (2030s and 2060s) against the control period (384 mm). From Figure 7 the highest decrease is pronounced in January, February, March during which major drought and water rationing have occurred previously. But in April the rain increases and compares well with the future rain. In fact from the month of April, the season gets wetter than the control period till the end of the season in July. This implies that future dry season is projected to be wetter than present-day dry season. This projected rainfall may improve the drought condition that often haunts the paddy scheme, and this is a significant finding of the study.

In the most severe scenario (RCP8.5) the overall seasonal rain is not changing significantly, although the seasonal effective rainfall is also decreasing during February to April compared to the control period. The rainfall during the 2030 period increase by 2% (392 mm) while there is no change in that of the 2060s. During the main growing season (wet season), effective rainfall shows an increasing trend of about 8% (586 mm) and 13% (619 mm) for RCP6.0 and RCP8.5 scenarios respectively against the control period. There is also no difference during the two future periods in both scenarios. Monthly rainfall changes evenly with a noticeable trend from August to November, and then a decreasing trend from December to January. The highest projected weekly effective rainfall is 33 mm contributed as irrigation and is found in September and November.

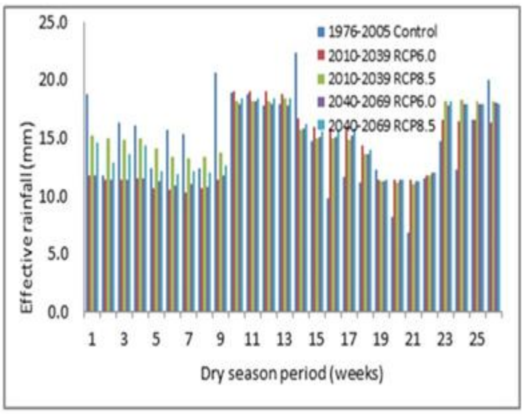
Based on these results, there is likely presence of increase in floods during the main rice growing season, as well as some intermittent dry spells during dry season period. This variation in rainfall in both seasons needs to be considered in water resource planning of the scheme.

Table 5 Summary of changes in rainfall parameters between control and future periods (the % indicates change from control)

Months	1976-2005 Control (mm)	2010-2039 (RCP6.0) (mm)	2040-2069 (RCP6.0) (mm)	2010-2039 (RCP8.5) (mm)	2040-2069 (RCP8.5) (mm)
Annual rainfall (mm)	1515	1601 (6%)	1621 (7%)	1721 (14%)	1721 (14%)
Change (%)					
Effective rainfall at wet season (mm)	537	586 (8%)	619 (13%)	580 (7%)	612 (12%)
Change (%)					
Effective rainfall (dry season) (mm)	384	365 (-5%)	365 (-5%)	392 (2%)	384 (0%)
Change (%)					
Rainy days during at wet season	56.6	63.3 (12%)	65.8 (16)	59.5 (5%)	58.4 (3%)
Change (%)					
Rainy days during dry season (days)	41.7	41.2	42.2	40.0	42.0
Change (%)		-1%	1%	-4%	1%
Wet-spell length (days)	1.4	1.4	1.4	1.4	1.4
Change (%)		0%	0%	0%	0%
Dry-spell length (days)	5.0	5.2	5.2	5.2	5.4
Change (%)		4%	3%	4%	7%

Changes in rainy days

Table 5 presents changes in number of rainy days during rice growing seasons under the two scenarios. The rainy days are projected to decrease very little (up to 4%) during the dry season under RCP6.0 for both 2030s and 2060s, and only just 1% increase under RCP8.5 scenario compared with control period. This implies that rainfall intensities will increase to account for the projected increased rains during this dry period. The same Figure also shows an increasing trend in the number of rainy days during both dry and wet rice seasons for both scenarios. The wet season rainy days percent increase is from 12% under RCP6.0 to 16% under the most severe scenario, RCP8.5, during the early years of the century (2010-2039), and is then reduced to 3% increase by 2040-2069 period.



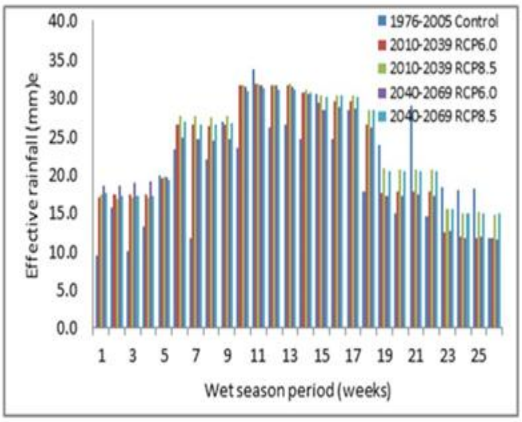


Figure 7 Comparison of future seasonal effective rainfall patterns against control period for (a) dry season (b) wet season

Changes in wet and dry -spell lengths

Wet and dry spell length is defined as the maximum consecutive wet or dry days for a particular month, and this definition has been adopted in this study. Dry spell series is given much attention in agriculture related studies as it can potentially hamper agricultural production. Table 5 summarizes average wet and dry spell lengths both growing seasons and Figure 8 presents the patterns against control period. The figure indicates that generally the wet spell pattern is unlikely to change in future for all RCP scenarios. The dry spell on the other hand, shows slight increase change from 3-7% for RCP6.0 and 8.5 respectively in comparison with the control baseline period but does not change significantly in real day terms. Traditional paddy scheduling practices in this scheme typically involves uniform application of 100 mm irrigation water every 7-10 days to maintain standing water on flooded rice system. This volume is exhausted in 10 days assuming a daily ET and seepage values of 7 and 3 mm/day. The results suggest that, for optimal utilization of rain water, on farm storage of rain water must be practiced often especially during the dry season to reserve rain water at field surface and in the soil profile.

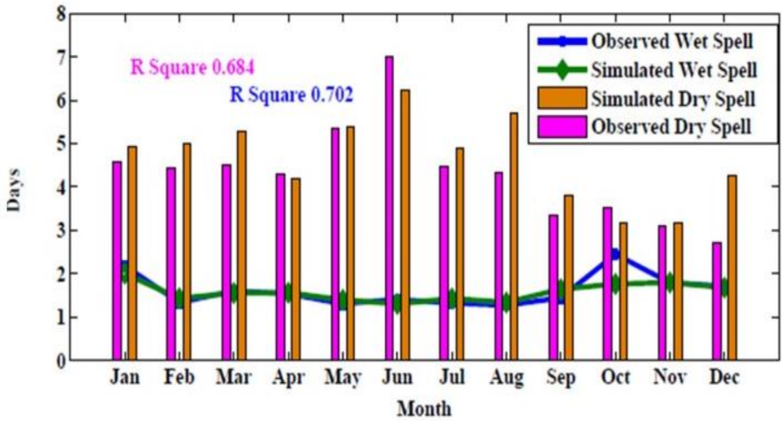


Figure 8 Comparison between control and simulated values of wet and dry spell lengths at station no3609012

4 SUMMARY AND CONCLUSION

Rainfall is an important component in paddy farming and therefore, knowledge on how it is likely to evolve in future is essential in the paddy growing areas of Malaysia. The current paper presents results on climate change impact on future daily rainfall by downscaling GCM simulations at grid point in a rice growing scheme.The climate scenarios were constructed from an ensemble of 10 climate models (GCMs) under the updated emission scenarios, RCP6.0 and 8.5 for control period as well as two future periods (2030s and 2060s). The WGEN-type stochastic rainfall generator model was adopted for downscaling and simulation of future rainfall for the irrigation scheme after calibration and testing. The GCM outputs were statistically downscaled using the change factor (delta change) method by perturbing the model parameters.

The results obtained are variable among GCMs indicating the existence of uncertainties in simulating future climate variables. However, they all agree in the direction of future changes in the rainfall scenario for the area. Most GCMs predicted a decreasing trend in future rainfall during dry season and an increase in the wet season, although one model predicted a significant decrease of up to 34% and 18% during the dry and wet seasons respectively. Overall future annual rainfall is projected to increase for all the future periods. The annual ensemble mean rainfall indicate an increase change of 6% for dry season to 14% during wet season for 2030s and 2060s future periods based on RCP 6.0 and RCP 8.5 scenarios.

Consequently, the projected future rainfall results follow a similar trend for seasonal effective rainfall. This is especially an important aspect of this study because the contribution of rainfall as irrigation water is judged on the basis of this parameter. The future effective rainfall is estimated to decrease by 5% in dry season under RCP6.0 and then increase slightly by 5% again during the wet season under the severe scenario. The irrigation scheme is anticipated to experience increased effective rainfall during wet season for all time periods especially in September and October. The most significant finding of the study is that the dry season will become wetter and the wet season will be even wetter. This is an area of concern that paddy farmers and water managers may want to keep alert to, so as to secure future irrigation water for the paddy sector. Based on the results, the following future implications can be drawn from the study with suggested options:

(1) *Occurrence of floods and droughts:* the future of paddy farming is likely to be faced with some floods during wet season due to increased rainfall events. And equally likely is occurrence of droughts in the dry season predicted to occur especially in the first 4 months. These changes will influence water resources planning for irrigation water for the scheme. Precaution is required to ensure that the rice crop is managed properly to reduce negative impacts.
(2) *Construction of storage reservoirs*: there is need to conserve rain water volume for subsequent use in the dry season as means to augment irrigation water supply during such a time.
(3) *Altering of paddy cropping schedule*: generally, it appears like the issue of climate change may not impose significant water shortages for paddy cultivation in terms of physical water shortages. The projected increase in rain water presents an opportunity of increasing rice production in the country with an additional cropping season, (5 seasons) in every 2 years. This can be obtained through changes in cropping patterns and alternative water management practices. Further study is required on the aspect of cropping schedules based on future rainfall distribution to achieve this purpose.
(4) *GCM uncertainties*: the wide spread in the climate models underscores the importance of multi-model application in climate change studies. It is widely recognized that each climate model has its own prediction representing a single projection of several future projections. As such, reliability of future climate scenarios depends largely on model resolution and these models are being improved. Therefore, future studies must aim to employ more and also improved climate models consistent with the time.
(5) *Paddy water requirements*: our projection of future rainfall represents our first attempt towards quantifying future paddy water requirements. Consequently, a proper study on future paddy irrigation water requirements for the scheme is warranted, as it was not covered in this present study because other climate data were not yet available.

Finally, the stochastic rainfall generator model was successful in downscaling GCM output and also establishes the direction of future rainfall changes. Although there is wide spread with some GCMs, the preliminary findings indicate some of the potential risks and/or opportunities that climate change could impose on paddy production in Malaysia. The expected changes in the rainfall regime, as highlighted above, require further work to conclude whether these changes have negative or positive meaning for rice production in this scheme. The information generated in this study therefore serves as useful baseline from which future studies can draw for further insights. Future effort is aimed at developing a water management-support tool for modeling water allocations and irrigation schedules in paddy fields.

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