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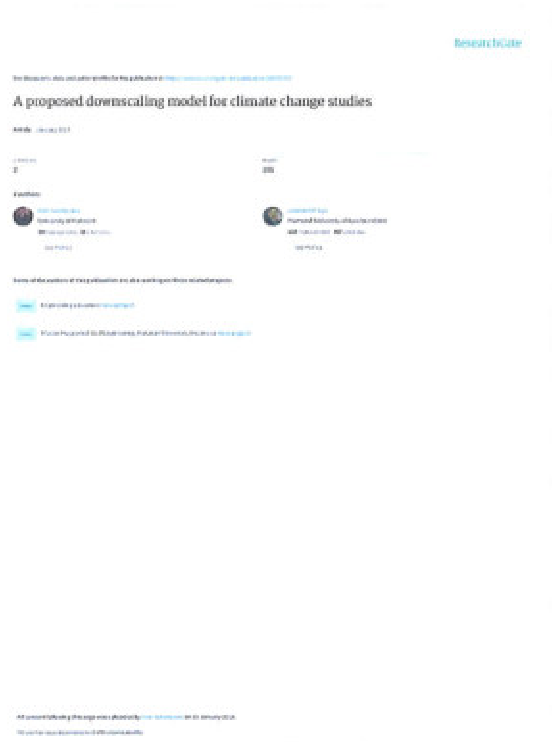
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by Heri Sulistiyono

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A proposed downscaling model for climate change studies


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A Proposed Downscaling Model for Climate Change Studies

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Abstract: General Circulation Models (GCMs) are commonly used to simulate future climate conditions in climate change studies. However the resolution from these models is too coarse for river basin scale studies. As such the results from these models need to be downscaled appropriately for use at the basin scale. Well known downscaling models include various dynamical and statistical approaches. However, none of these has been officially recommended as the best model for use in all regions. Disadvantages of existing downscaling models include high cost of operation, inability to avoid producing unrealistic values, inability to include multiple variables, and inability to reflect the future change of variability. In this paper, the development of a new downscaling model is based on a **hy**brid of **a**lgebraic and **s**tochastic approaches that can include multiple variables is proposed. This new model will be called the HYAS model. HYAS employs the differences between simulated future and baseline variables added to simulated changing residual variance. This new approach has been applied in a climate change study of the Jangkok River Basin in Lombok, Indonesia. Twenty years (1971 to 1990) of GCM outputs were set as baseline variables and were used in the calibration process. The subsequent, twenty years (1991 to 2010) of data were used for model validation. Then, the relevant GCM outputs from 2011 to 2100 were used as model predictors to simulate the following regional climatic variables: humidity, rainfall, sunshine, temperature, and wind speed. Results showed that the following GCM variables: Screen 2m Temperature, Screen Specific Humidity, and Skin Temperature are appropriate for modeling regional humidity, rainfall, sunshine, and air temperature. However for modelling regional wind speed, the following GCM variables: Evaporation, Screen 2m Temperature, and Surface Pressure are more appropriate. The HYAS model is found to be superior to existing methods for predicting regional climatic variables in the Jangkok River Basin.

1. Introduction

As reported in IPCC (2001), there have been many disasters that have destroyed residences, dams, roads, bridges, farms and many other facilities and have caused huge of financial losses around the world. These disasters have brought crucial questions as to what factors have triggered, and how to adapt to these disasters. It is believed that some of the recent disasters were related to climate change. Climate information plays an important role in answering questions such as: how large should agricultural land be developed in a particular basin; how many hours of wind are required to sustain a wind-driven generator; and what is the designed height of embankments to protect a town from floods. In water resource studies, designs are directly depend on the following climatic information: precipitation, temperature, humidity, wind, net radiation, groundwater, and stream-flows. These variables control water availability (Dingman, 2002; Viessman, 2003; and Tallaksen and Van Lanen, 2004).

Information about global climate change based on emission scenarios has been simulated using General Circulation Models (GCMs); however, given the coarse resolutions, an enormous challenge is posed in utilizing these long-term outputs for any meaningful regional or local climate change studies (IPCC, 2007). In light of this shortcoming, it becomes necessary to deploy downscaling models in order to simulate future climate change scenarios at finer spatial scales, which are more adaptable for regional climate change studies. Many researchers including Schnur and Lettenmaier (1996), Wilby et al., (2004), Cannon (2006), and Lopes (2009), among others, have investigated and applied currently available approaches to GCM downscaling. These methods include dynamical and statistical approaches. However none of the current approaches has been found to be always best in all cases. Some of the disadvantages of current approaches include high cost of operations, inability to incorporate changing variability in the future, inability to avoid producing some impossible variables, inability to include multiple variables, and difficulty in satisfying essential assumptions (Pfizenmayer and von Storch , 2001; Wilby et al, 2004). This paper have three objectives: 1) to obtain suitable GCM variables for simulating regional climatic variables; 2) investigate current downscaling approaches for suitability in the region of interest, and 3) to develop a new downscaling model that can include multiple variables for simulating regional hydrologic and climatic variables. The climate change scenarios for the Jangkok River Basin in Lombok Island, Indonesia will be used as a case study.

2. Methodology

Existing downscaling models include: the Change Factor method, Dynamical models, and Statistical models (Pfizenmayer and von Storch, 2001; Wilby et al., 2004; Timbal et al., 2009). Given the disadvantages of existing downscaling models, a new downscaling model will be developed in this paper. This new model will consider more than one GCM variable (at least two GCM variables) to increase the information content. According to Wilby et al. (2004), the most important GCM variable in the development of regional downscaling model is temperature, either Screen (2m) Temperature (°C) or Skin (surface) Temperature (°C). However, in this paper some other GCM variables as shown in Table 1 will also be selected as they may give some other information such as trends and possible variability. The selection of the appropriate GCM variables to include is based on sensitivity analysis. In this paper, the GCM variables are listed in Table 1. The schematic diagram shown in Figure 1 gives a better understanding of the links among the various proposed procedures.

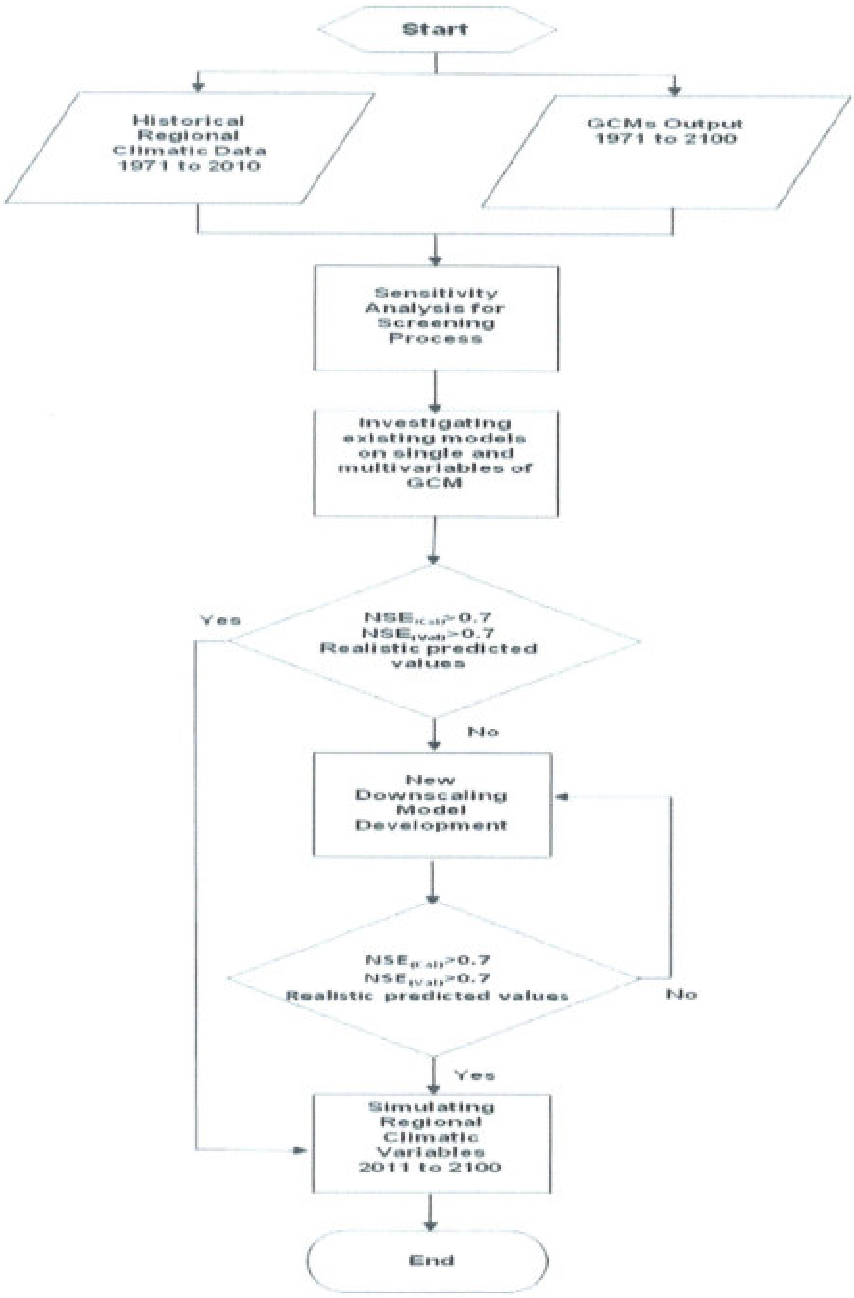

Figure 1: Schematic Diagram for the Proposed Study

Table 1: GCM Variables involved in the proposed model

Notation	Description	Units
X1	Mean 2m Wind Speed	m/s
X2	Evaporation	mm/day
X3	Precipitation	mm/day
X4	Screen (2m) Temperature	°C
X5	Screen Spec. Humidity	kg/kg
X6	Sea Level Pressure	hPa
X7	Skin (surface) Temperature	°C
X8	solar flux at surface	W/m^2
X9	Surface Pressure	hPa

Three methods of sensitivity analysis: Neural Networks, Standardized Regression Coefficients, and Correlation Coefficients will be used in a screening process to select the sensitive GCM variables that will be involved in the development of the new downscaling model. The description of neural networks, standardized regression coefficients, and correlation coefficients has been explained in many text books. Their applications can also be found in McCuen (1993), Stergiou and Siganos (1996), and Ji (2004) and therefore will not be described in this paper.

The proposed downscaling model is based on a hybrid of algebraic and stochastic approaches and thus named the HYAS model. It is expressed as

[1] $\hat{Y}_i = Y_i + sign[r] * K * \frac{\sum_{j=1}^{n}(Z_{j(s)} - Z_{j(m)})}{n} + C * \varepsilon_{(i)}$, if $\frac{\sum_{j=1}^{n}(Z_{j(s)} - Z_{j(m)})}{n} = G_i$, then

[2] $\hat{Y}_i = Y_i + sign[r] * K * G_i + C * \varepsilon_{(i)}$, if $Y^*_i = Y_i + sign[r] * K * G_i$, then

[3] $\hat{Y}_i = Y^*_i + C * \varepsilon_{(i)}$

Where:

$\hat{Y}_i$	=	downscaled regional variable,
Y_i	=	baseline regional variable,
C	=	residual rescaling coefficient
Y^*_i	=	calculated regional variables before being added to generated residuals,
r	=	sign of correlation between the baseline of GCM and regional variables,

K	=	standardized GCM variables rescaling coefficient,
$Z_{j_{t,i}}$	=	standardized GCM variable of i in the next j year (future period),
$Z_{j_{b,i}}$	=	standardized GCM variable of i in the baseline period,
ε_i	=	generated model residuals with changing mean and variance,
j	=	the number of GCM variables.

The purpose of the residual rescaling coefficient (C) is to adjust the range of predicted regional variables so that it will not go beyond the limit of possible values. If none of the predicted regional variables lies beyond the boundary, $C = 1$; if at least one of the predicted regional variables lie beyond the boundary, the value of C will be between 0 (zero) and 1 (one) and can be obtained by calibration. Model acceptance criteria are used to judge whether the new model can satisfactorily replace the currently used models. A new model will be accepted only if it satisfies the criteria proposed in Table 2.

Two methods of residual generation can be used: artificial neural networks (ANN) and a cluster based approach were developed as a part of HYAS model to generate residuals that have a varying mean and variance. Using an ANN approach, residual generation requires the input variables of GCM, normal random variates, and Y^*. If the cluster approach is used, residual generation requires 9 steps: (1) clustering the residuals found in the calibration process based on a monthly order to eliminate the time dependency of residuals; (2) regressing the clustered residuals to time to obtain the slope of the change of residuals; (3) determining the new residuals obtained from the regression in step 2; (4) transforming the new residuals into a normally distributed variate; (5) determining the parameters (μ, σ) of the normally distributed residuals found in step 4, (6) generating a new random variable based on a normal distribution with mean zero and standard deviation of σ which was found in step 5; (7) inverse transforming the normally distributed variables based on the type of transformation used in step 4; (8) adding the transformed residuals to the regression equation of step 2; and (9) anti-clustering the results of step 8 into the original sequences.

Table 2: Model Acceptance Criteria

No	Criteria	Range of Acceptance
1	Goodness of fit (model validation)	NSE > 0.7
2	Realistic range of simulated results	Regional Humidity (%) = 0 ~ 100 Rainfall (mm) = 0 ~ + infinity Sunshine (%) = 0 ~ 100 Air Temperature ($^{\circ}$C) = − infinity ~ + infinity Wind Speed (knots) = 0 ~ + infinity
3	Statistical characteristics	Presence of changing future mean and variability.

In the development of a model, model goodness of fit tests is an important step both in calibration and in validation processes. Measures of goodness of fit will summarize the discrepancy between observed variables and the variables expected from the model (Sorooshian and Gupta, 1995). The goodness of fit test that will be used in this study is the Nash- Sutcliffe Model Efficiency Coefficient (NSE) (Nash and Sutcliffe, 1970).

3. Results

According to IMF (2011), the world's population in 2050 has been predicted to reach 8.9 billion. Moreover in Padmanabhan (2010), new technologies cannot be easily and directly applied in some countries or particular regions due to cost, means of support, applicability, and language issues. In addition, from analysis based on a matrix correlation of 66 representative countries, it is found that economic growth of countries around the world is regional; therefore, this study employed the A2 emission scenario to simulate the possible change of regional hydrologic and climatic variables and to study the impacts of global climate change.

Table 3: Sensitivity Based Screening Process of GCM variables for the regional humidity model

REGIONAL HUMIDITY MODEL							
	ANN		SRC		CC		Average
Inputs	Importance	Ranking	Coefficient	Ranking	Coefficient	Ranking	Ranking
X1	0.027	4	-0.353	6	-0.091	6	4
X2	0.019	5	0.412	5	-0.023	8	6.5
X3	0.004	8	0.0508	9	0.149	5	8
X4	0.319	2	1.85	2	0.222	2	2
X5	0.127	3	0.935	3	0.231	1	3
X6	0.005	6	0.449	4	-0.088	7	5
X7	0.493	1	-2.64	1	0.215	3	1
X8	0.001	9	-0.0849	8	-0.08	9	9
X9	0.004	7	-0.314	7	-0.17	4	6.5

In Table 3, GCM variables are ranked based on their sensitivity to the change of model outputs. Their sensitivity is recognized from importance in the ANN method, and from coefficients of standardized regression (SRC) and correlation (CC). The average of the three rankings is used as the grand rank of GCM variables. The top three most sensitive GCM variables are then selected for modelling the regional humidity variables. The top three most sensitive GCM variables for modelling regional humidity are X4 (Screen 2m Temperature), X5 (Screen Specific Humidity), and X7 (Skin Temperature). The top three most sensitive GCM variables for modelling the other regional variables are presented in Table 4.

Table 4: Sensitivity Based Screening Process of GCM variables for the other regional models

Ranking of significant GCM Variables				
Inputs	Rainfall	Sunshine	Air Temperature	Wind Speed
X1	8	6	5	6.5
X2	6.5	5	4	3
X3	9	9	9	8
X4	1	1	2	6.5
X5	3	2	3	1
X6	4.5	7	7.5	5
X7	2	3	1	4
X8	6.5	8	7.5	9
X9	4.5	4	6	2

From Tables 4 the top three most sensitive GCM variables for modelling regional rainfall, sunshine, and air temperature are similar to the top three most sensitive GCM variables for modelling regional humidity, which are X4 (Screen 2m Temperature), X5 (Screen Specific Humidity), and X7 (Skin Temperature). The top three most sensitive GCM variables for modelling regional wind speed are X2 (Evaporation), X5 (Screen 2m Temperature), and X9 (Surface Pressure).

Table 5: The range of predicted variables from simulations

Regional Variables	Ranges		ANN		CF		LR		NLR	
	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min
Humidity (%)	100	0	85.1	75	88.7	85	89.5	76.3	90.1	76.4
Rainfall (mm)	+ inf	0	989	7	590	7	456	-27	2516	26
Sunshine (%)	100	0	94	38	96	38	89	39	89	41
Air Temp(°C)	+ inf	- inf	36.7	22.8	29.9	22.8	28.8	24.7	28.7	24.7
Wind Speed (knots)	+ inf	0	22.6	1.9	29.6	2.1	5.3	5	5.3	5

....Table 5 continued

Regional Variables	Ranges		MANN		MLR		MNLR		HYAS	
	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min
Humidity (%)	100	0	178.9	64.2	85	75	91.1	76.4	100	75
Rainfall (mm)	+ inf	0	1700.5	-1500	363.1	-7	516.5	-7.4	619	7
Sunshine (%)	100	0	164	-159	96	38	89	58	98	33
Air Temp(oC)	+ inf	- inf	37.8	8.7	30	23	29.7	24.8	33	24
Wind Speed (knots)	+ inf	0	12	-6	9	3	6	4	13	3

Table 5 shows that only ANN, CF, and HYAS produced realistic variables. The next investigation is based on the performance of those models (based on NSE) in the processes of calibration, validation, and the Akaike Information Criterion as shown in Table 6. The best model is chosen based on higher NSE and lower AIC when comparing single to multiple variable models.

Table 6: Investigation of Existing Downscaling Models

	Downscaling Models	Humidity cal/val/AIC	Rainfall cal/val/AIC	Sunshine cal/val/AIC	Temperature cal/val/AIC	Wind Speed cal/val/AIC
Simple	ANN	0.86/0.6/-459	0.99/0.78/1448	0.98/0.66/64	0.99/0.81/- 86	0.52/-0.24/-526
	CF	1/0.37/	1/0.16/	1/0.5/	1/0.75/	1/-0.85/
	LR	0.66/0.27/181	0.67/0.5/2867	0.5/0.44/1454	0.6/0.58/-50	0.01/- 0.07/-326
	NLR	0.66/0.22/190	0.69/- 0.12/2864	0.49/0.44/1457	0.62/0.57/-54	0.01/- 0.06/-326
Multiple	MANN	0.8/- 4.9/568	0.77/- 0.06/3101	0.51/0.33/1579	0.78/0.32/- 186	0.47/0.01/-288
	MLR	0.66/- 0.49/213	0.72/0.45/2874	0.5/0.49/1377	0.61/0.54/-423	- 0.6/- 1.38/-377
	MNLR	0.67/- 0.33/247	0.68/-0.32/2723	0.5/0.26/1225	0.66/0.47/-510	0.35/- 0.88/-382
	HYAS	0.95/0.73/	0.98/0.78/	0.96/0.75/	0.97/0.72/	0.93/0.73/

Where: ANN = Artificial Neural Networks model, CF = Change Factor method, LR = Linear Regression approach, NLR = Non Linear Regression approach, MANN = Multiple Artificial Neural Networks model, MLR = Multiple Linear Regression approach, MNLR = Multiple Non Linear Regression approach, HYAS= Hybrid of Algebraic and Stochastic approach, and cal/val/AIC = calibration/validation/Akaike Information Criterion.

Table 6 showed that the ANN model gave the best results in calibration and validation among the simple models. However among multiple models, the HYAS model performs best. Since one of the objectives of this study is to develop a model that can incorporate multiple variables, the HYAS model is selected as the best model with multiple variables. Furthermore, as one common requirement of climate change model is to be able to incorporate changing variability in the future, the HYAS model was also shown to be able to actually produce a varying mean and variance of the simulated variables. Varying mean and variance of simulated regional climatic variables using the HYAS model are shown in Figures 2 and 3.

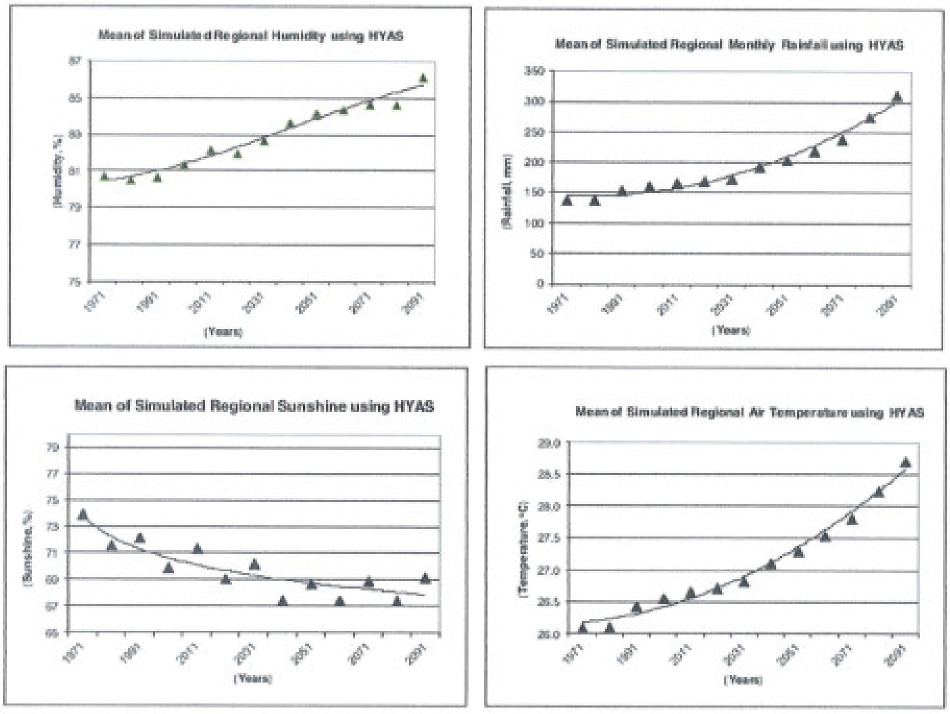

Figure 2: Mean of simulated regional climatic variables.

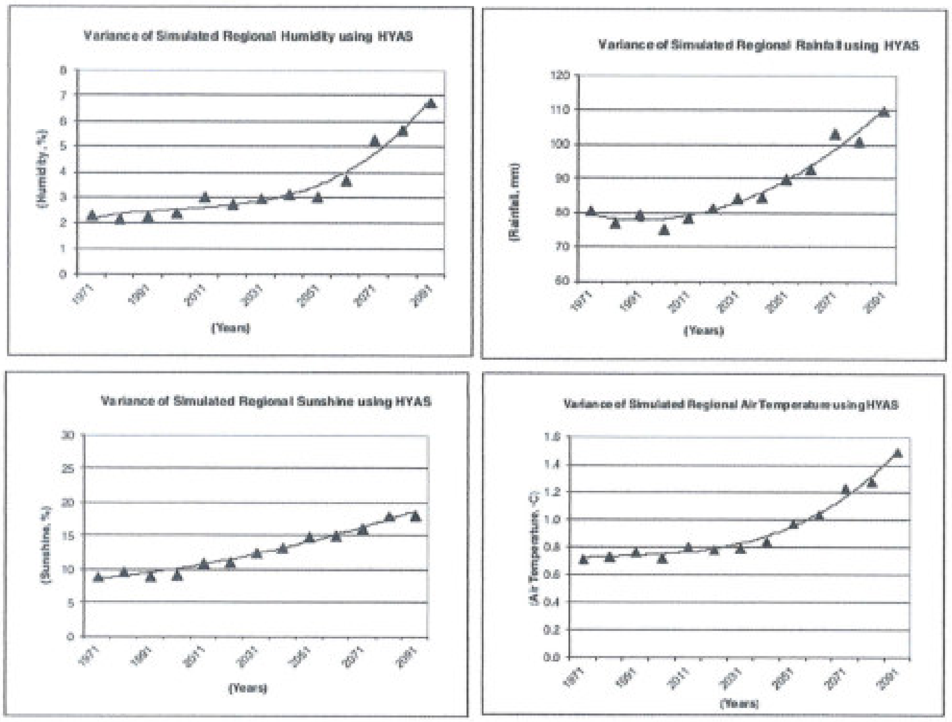

Figure 3: Variance of simulated regional climatic variables.

4. Conclusion

1. Screen Specific Humidity, Screen Temperature, and Surface Temperature are the top 3 most sensitive GCM variables to model regional climatic variables in the region of interest.
2. The ANN model gave the best results in calibration and validation among the simple models.
3. The new downscaling HYAS model gave better performance compared to existing methods for simulating regional variables in the region of interest using multiple GCM variables. In addition, the methods of ANN and cluster based approaches were successfully developed to utilize HYAS models to produce varying means and variances of future regional variables.

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PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6

PAGE 7

PAGE 8

PAGE 9

PAGE 10

PAGE 11