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A Dynamic Equation for Downscaling Surface Air Temperature

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***Abstract*—**In order to utilize results from global climate models, dynamical and statistical downscaling techniques have been developed. For dynamical downscaling, usually a limited area numerical model is used, with associated high computational cost. This research proposes dynamic equation for specific space-time regional climate downscaling from the Educational Global Climate Model (EdGCM) for Southeast Asia. The equation is for surface air temperature. This equation provides downscaling values of surface air temperature at any specific location and time without running a regional climate model. In the proposed equations, surface air temperature is approximated from ground temperature, sensible heat flux and 2m wind speed. Results from the application of the equation show that the errors from the proposed equations are less than the errors for direct interpolation from EdGCM.

***Keywords*—**Dynamic Equation, Downscaling, Inverse distance weight interpolation.

NOMENCLATURE

EdGCM	= Educational Global Climate Model
GCMs	= Global Climate Models
IDW	= Inverse Distance Weight
Dyn	= The value from dynamic equation
EdG	= The value from EdGCM

I. INTRODUCTION

STUDY of climate change is an important factor for future human life all over the world. Climate information at regional or local scales is important for potential impact of climate changes on societies and ecosystems. Therefore, it is important to predict the future climate to prepare for protection from the destruction, and also to utilize the benefits that the phenomena may bring. The future climate changes are described by outputs of Global Climate Models (GCMs) which use mathematical equations to describe the dynamic of climate system for projections of future climate. Because GCMs have coarse resolution, the outputs from GCMs cannot directly apply to specific areas for climate change study. Therefore, mathematical and/or statistical methods are needed to downscale the outputs of GCMs to local areas. Downscaling method is the process that takes data at coarse resolution to make prediction at finer resolution (local scale). There are two kinds of downscaling methods, dynamical and statistical downscaling.

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Dynamical downscaling uses numerical model with higher resolution than GCMs, therefore it is able to simulate local conditions in greater detail [1], [2]. Statistical downscaling is a two steps process. First, development of statistical relationship between large scale variables and a local variable. Second, the application of such relationship to the output of GCM experiments to simulate local climate characteristics in the future [3]-[5].

In this study, dynamical downscaling is applied to the outputs from Educational Global Climate Model (EdGCM). The outputs from EdGCM are downscaled to Thailand using the proposed dynamic equation for prediction of surface air temperature.

II. NUMERICAL METHOD

A. Problem Setup

Objective of the present paper is to using the proposed dynamic equation for prediction of surface air temperature. Dynamic equation is used to approximate the downscaling value of surface air temperature at the gird points of EdGCM that cover the specific location of interest is shown in Fig. 1. IDW have been made for interpolation downscaling values of surface air temperature at any specific location and time without running a regional climate model.

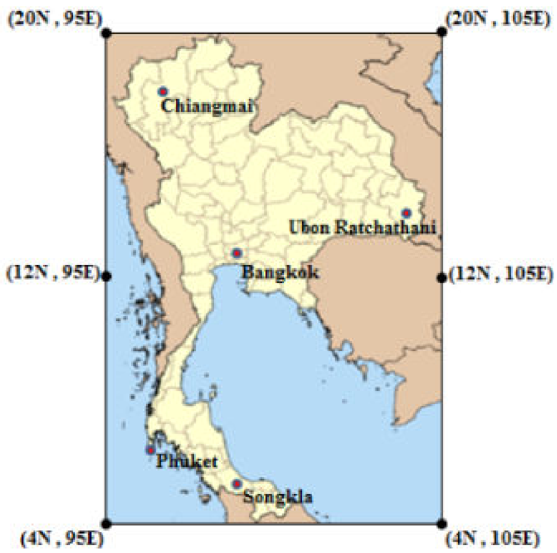


Fig. 1 The points of interest, Chiangmai, Ubon Ratchathani, Phuket and Songkla, and the grid points of EdGCM that cover the points of interest

B. Educational Global Climate Model

The climate model used in this research is the Educational Global Climate Model (EdGCM) developed by NASA's Goddard Institute for Space Studies (NASA/GISS) and the global warming scenario is Global_Worming_01.

EdGCM software is a 3 dimensional atmosphere-ocean model. The model numerically solves five fundamental physical equations which are the conservation of mass, energy, momentum and moisture and the ideal gas law in each cell, while taking into account the transport of quantities between cells. GCM divides the atmosphere into a series of discrete grid cells. EdGCM model has 7,776 grid cells in the atmosphere which is 8° latitude by 10° longitude (as shown in Fig. 2), containing 9 vertical layers [6], two ground layers (one to model surface absorption and one to model deep ground properties) and two ocean layers. Calculations for each grid cell are iterated in fifteen-minute (simulation time) time steps throughout the duration of the simulation [7].

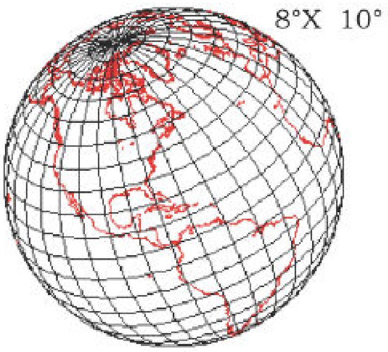


Fig. 2 EdGCM grid resolutions expressed in degrees of latitude and longitude [6]

The basic equations of EdGCM [6], these five equations are

$$\frac{\partial \vec{V}}{\partial t} = -\left(\vec{V} \bullet \nabla\right)\vec{V} - \frac{1}{\rho}\nabla p - g - 2\vec{\Omega} \times \vec{V} + \nabla \bullet \left(k_m \nabla \vec{V}\right) - \vec{F}_d$$

$$\rho C_p \frac{\partial T}{\partial t} = -\rho C_p \left(\vec{V} \bullet \nabla\right) T - \nabla \bullet \vec{R} + \nabla \bullet \left(k_\tau \nabla T\right) + C + S$$

$$\frac{\partial \rho}{\partial t} = -\left(\vec{V} \bullet \nabla\right)\rho - \rho\left(\vec{V} \bullet \nabla\right)$$

$$\frac{\partial q}{\partial t} = -\left(\vec{V} \bullet \nabla\right) q + \nabla \bullet \left(k_q \nabla q\right) + S_q + E$$

$$p = \rho R_d T$$

where $\vec{V}$ is velocity, T is temperature, p is pressure, ρ is density, q is specific humidity, g is gravity, $\vec{\Omega}$ is rotation of earth, $\vec{F}_d$ is drag force of earth, $\vec{R}$ is radiation vector, C is conductive heating, c_p is heat capacity for const., $p\,E$ is evaporation, S is latent heating, S_q is phase-change source, k is diffusion coefficients, R_d is dry air gas constant.

C. Dynamic Equation

The dynamic equation is determined by mean wind speed, sensible heat flux and ground temperature.

The bulk formula for the sensible heat flux (H_s) in the surface layer is [8]

$$H_s = \rho C_p \overline{W'T'} \tag{1}$$

The vertical flux F_ξ of any variable ξ is assumed to be driven by the difference in $\bar{\xi}$

$$F_\xi = \overline{W'\xi'} = -U(\bar{\xi}_{top} - \bar{\xi}_{bottom})$$

where U represents a transport speed across that interface, and the $\bar{\xi}_{top}$ and $\bar{\xi}_{bottom}$ are the values just above and below the boundary of the surface layer. Therefore, the heat flux is shown as

$$\overline{W'T'} = -U(\bar{T}_s - \bar{T}_g) \tag{2}$$

where $\bar{T}_g$ and $\bar{T}_s$ are mean ground temperature and mean surface air temperature.

The transport speed (U) is usually parameterized as a function of some measure of turbulence.

$$U = C_H \cdot \overline{M(z)} \tag{3}$$

where C_H is transfer bulk coefficient for sensible heat and $\overline{M(z)}$ is the mean wind speed at the height z. $\overline{M(z)}$ can be calculated by logarithmic wind profile [9], the expression is

$$\overline{M(z)} = \frac{u_*}{k}\ln\left(\frac{z}{z_0}\right) \tag{4}$$

where u_* is frictional velocity, and z_0 is surface roughness.

$$u_*^2 = C_D M^2{}_{ref}$$

where M_{ref} is the wind speed at the reference level (10 m).

For momentum transfer, C_D is called bulk transfer coefficient for the same height. The relationship between bulk transfer coefficient for the same height, measurement height and surface roughness (z_0) under statically neutral conditions in the surface layer over land and ocean is

$$C_D = k^2 \cdot \left[\ln\left(\frac{z_{ref}}{z_0}\right)\right]^{-2} \tag{5}$$

where z_{ref} is the height at the reference level (10 m).

The mean wind speed (4) is given by replacing

$u_* = \sqrt{C_D M^2{}_{ref}}$ from (4)

$$\overline{M(z)} = \frac{\sqrt{C_D M^2{}_{ref}}}{k} \ln\left(\frac{z}{z_0}\right)$$

$$\overline{M(z)} = \frac{\sqrt{k^2 \cdot \left[\ln\left(\frac{z_{ref}}{z_0}\right)\right]^{-2} M^2{}_{ref}}}{k} \ln\left(\frac{z}{z_0}\right)$$

$$\overline{M(z)} = M_{ref} \frac{\ln(z/z_0)}{\ln(z_{ref}/z_0)} \tag{6}$$

Therefore, by replacing $U = C_M \overline{M(z)}$, the heat flux in the surface layer is shown in (7):

$$\overline{W'T'} = -C_M \cdot \overline{M(z)} \cdot (\overline{T}_s - \overline{T}_g) \tag{7}$$

That is, the heat flux (H_s) can be computed from

$$H_s = -\rho C_p C_M \cdot \overline{M(z)} \cdot (\overline{T}_s - \overline{T}_g) \tag{8}$$

Equation (8) is divided by (1)

$$1 = \frac{-C_M \cdot \overline{M(z)} \cdot (\overline{T}_s - \overline{T}_g)}{\overline{W'T'}}$$

$$C_M = \frac{-\overline{W'T'}}{\overline{M(z)} \cdot (\overline{T}_s - \overline{T}_g)}$$

where $\overline{W'T'} = \frac{H_s}{\rho C_p}$

$$C_M = \frac{-H_s}{\rho C_p \overline{M(z)} \cdot (\overline{T}_s - \overline{T}_g)}$$

The mean surface air temperature is shown as

$$\overline{T}_s = \overline{T}_g - \frac{H_s}{\rho C_p C_M \overline{M(z)}} \tag{9}$$

D. Inverse Distance Weight

The inverse distance weight (IDW) is a method for estimation the value at an unsampled point using a linear combination of values at sampled points weighted by an inverse distance function from the sampled points to the point of interest [10]. The assumption is the unsample point value will be most influenced by the nearest sampled point while more distant sample points will have less influence on determining the unsampled point value**.** The importance of a sampled point is represented by a non-negative numerical coefficient and the sum of weights is equal to one. In this research, weighting is determined from distance between the point of interest and the selected EdGCM grid points that cover the point of interest. That is, the inverse distance weight, λ, of an unsampled point *i* is defined as

$$\lambda_{ij} = \frac{1/d_{ij}}{\sum_{j=1}^{m} 1/d_{ij}} \tag{10}$$

where d_{ij} is distance between the unsampled point *I* and the sampled point *j*

$$d_{ij} = \sqrt{\left(latitude_{sample_j} - latitude_{unsample_i}\right)^2 + \left(longitude_{sample_j} - longitude_{unsample_i}\right)^2}$$

m is number of sampled points used for interpolation

III. The Experiment

The experiments are performed to downscale surface air temperature. The experiment cases are present climate (2001-2010) and future climates between the years 2021-2100 which is divided into10-year intervals (2021-2030, 2051-2060, 2081-2090 and 2091-2100). For the present climate, two sets of data for April (summer), August (rainy season) and December (winter) are used for the 5 provinces of Thailand. For downscaling of surface air temperature, the first data set is the simulation outputs from EdGCM. This data set is used to calculate surface air temperature. The variables used are monthly mean sensible heat flux, ground temperature and wind speed. The experiment cases are Case Ps for the present years and Case F for the future years. The second set is observed data (from meteorological stations) of monthly mean 850 hPa surface air temperature at the points of interest.

TABLE I
Experiment Cases of Surface Air Temperature

Cases	Years
Case P	2001-2010
Case F	2021-2030
EdGCM	2001-2010

The steps for the experiments are shown in Fig. 3. The experiments are started by deriving the related dynamic equations. Next, calculate surface air temperature at the EdGCM grid points using the dynamic equations obtained from The set of variables used as inputs in the surface air temperature downscaling by the temperature dynamic equation consist of monthly mean of sensible heat flux, ground temperature and wind speed from the outputs of EdGCM. Next, apply the inverse distance weighted interpolation as shown in (10) for the points of interest using the results from the dynamic equations at the grid points (A-F) of EdGCM. Finally, compare mean average error of surface air temperature obtained from the inverse distance weighted of the dynamic equations and EdGCM with the observations.

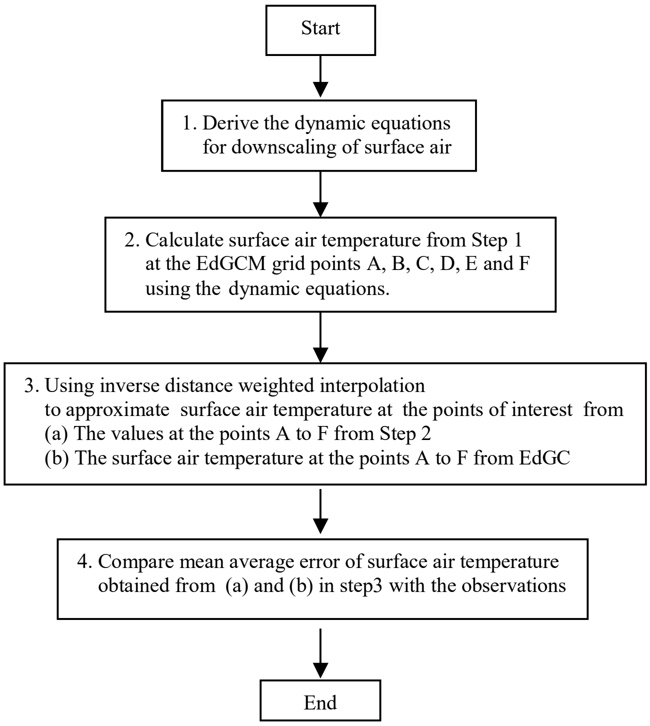
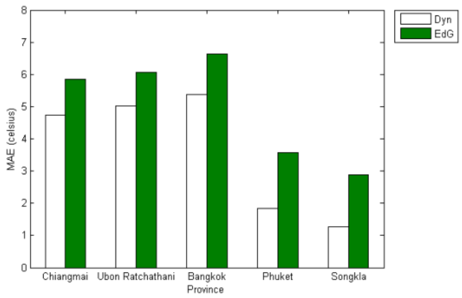


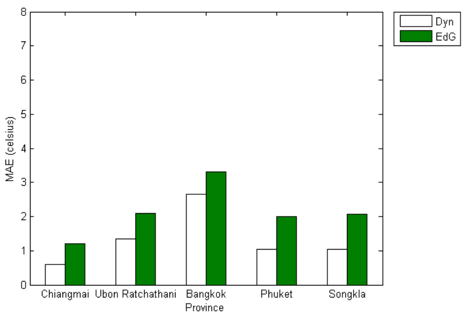
Fig. 3 The steps for downscaling of surface air temperature at the points of interest

IV. Results and Discussions

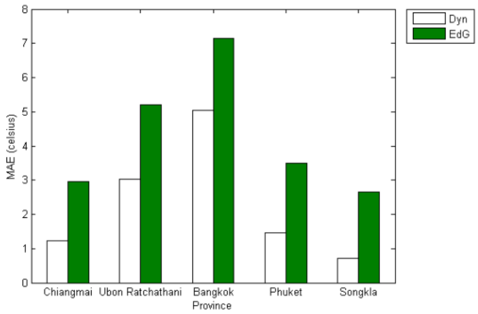
The downscaled surface air temperature for April, August and December can be calculated by (9), it depends on mean wind speed, sensible heat flux and ground temperature. Table II shows the mean surface air temperature from EdGCM.



(a) April



(b) August



(c) December

Fig. 4 MAE of surface air temperature for the present climate

Surface air temperatures for 2001-2010 are calculated by the dynamic equation for surface air temperature (9) and then IDW (10) is used for interpolation to Chiangmai, Ubon Ratchathani, Bangkok, Phuket and Songkla. Monthly mean surface air temperature for April, August, and December are shown in Table III.

TABLE II
MEAN SURFACE AIR TEMPERATURE (^{o}C)

Month	Point					
	A	B	C	D	E	F
April	22.9	22.3	26.2	25.1	26.2	26.9
August	25.3	24.5	27.3	25.7	26.5	26.3
December	18.4	13.0	25.1	21.8	25.1	25.0

TABLE III
MEAN SURFACE AIR TEMPERATURE (^{o}C) FOR THE PRESENT CLIMATE

Month	Average	Average Minimum	Average Maximum
April	26.3	25.8	27.0
August	26.8	26.4	27.3
December	23.6	25.1	22.0

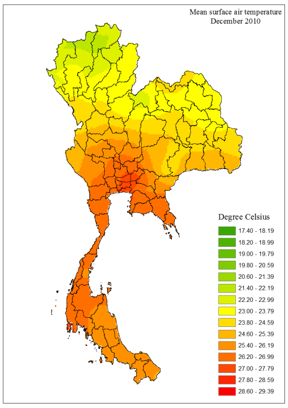
Fig. 4 shows MAE when compare with observation of the dynamic equation values and EdGCM data for the 5 provinces, for April, August and December, respectively. From the figures, EdGCM value has larger MAE than dynamic equation value. That is the dynamic equation for surface air temperature equation provides less error than the direct interpolation from EdGCM.

Fig. 5 presents surface air temperature of December 2010 with associated errors.

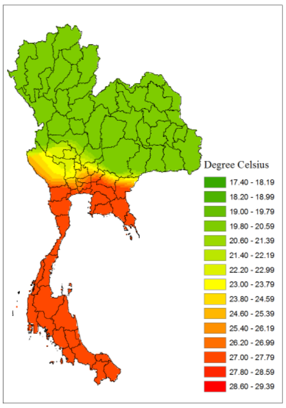
TABLE IV
MEAN DYNAMIC EQUATION ERROR OF SURFACE AIR TEMPERATURE FOR APRIL, AUGUST, AND DECEMBER

	April	August	December
Min	0.50	0.02	0.04
Max	6.10	2.80	4.60
Mean	4.30	1.30	2.10
Std dev.	1.40	0.50	1.10

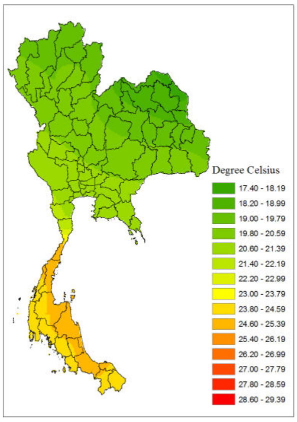
From (9), surface air temperature depends on sensible heat flux, ground temperature, and wind speed. Because mean sensible heat flux over land is more than over water, this results in surface air temperature over land to be more than over water. Results of the surface air temperature for April, August and December show that the dynamic equation error is less than the EdGCM error, as shown in Tables IV-V.



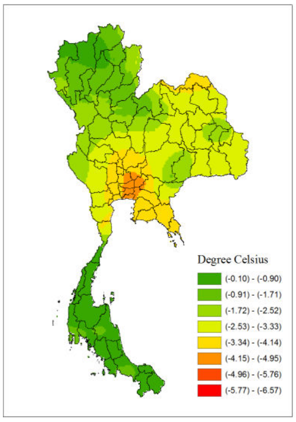
(a) Observed



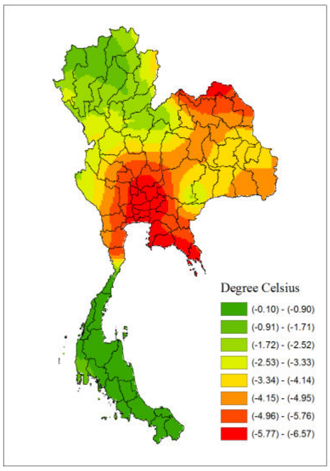
(b) Dynamic equation



(c) EdGCM



(d) Dynamic error



(e) EdGCM error

Fig. 5 Surface air temperature for December 2010, observed (a), dynamic downscaling (b), direct interpolation from EdGCM (c), dynamic error (dynamic-observed) (d) and EdGCM error (EdGCM-observed) (e)

TABLE V
MEAN EDGCM ERROR OF SURFACE AIR TEMPERATURE FOR APRIL, AUGUST, AND DECEMBER

	April	August	December
Min	2.00	0.60	1.40
Max	7.30	3.40	6.70
Mean	5.50	2.00	4.10
Std dev.	1.30	0.50	1.30

V. CONCLUSION

Climate change is a global phenomenon, but different regions of the world could experience different impacts from global climate change. However, climate models are not designed for specific place and time. In order to study specific space-time climate change, a downscaling technique is required. The dynamic equation is developed; the surface air temperature is a function of ground temperature, sensible heat flux, and wind speed at 2 m from the ground. The dynamic equation is applied for downscaling of surface air temperature at 5 locations in Thailand with the same years and months as in the case. The results also show that the dynamic equation provide better value for downscaling than the direct interpolation from EdGCM model.

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