CHAPTER 3 METHODOLOGY

3.1 The Educational Global Climate Model

The climate model applied in this study is Educational Global Climate Model (EdGCM). It is a three dimensional computer model that divides the atmosphere into a series of discrete grid cells. The EdGCM's model grid has 7,776 grid cells which is corresponding to 8° × 10° latitude by longitude in horizontal column (Figure 3.1) and containing 9 vertical layers in the atmosphere (Chandler et al., 2006).

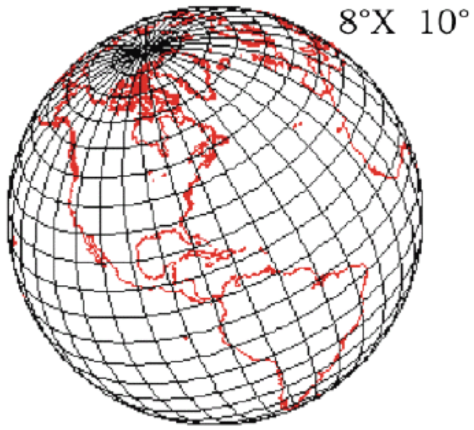

Figure 3.1 NASA/GISS Global Climate Model grid resolutions of 8° × 10° latitude by longitude (Chandler et al., 2006).

The procedure for running EdGCM is as follows.

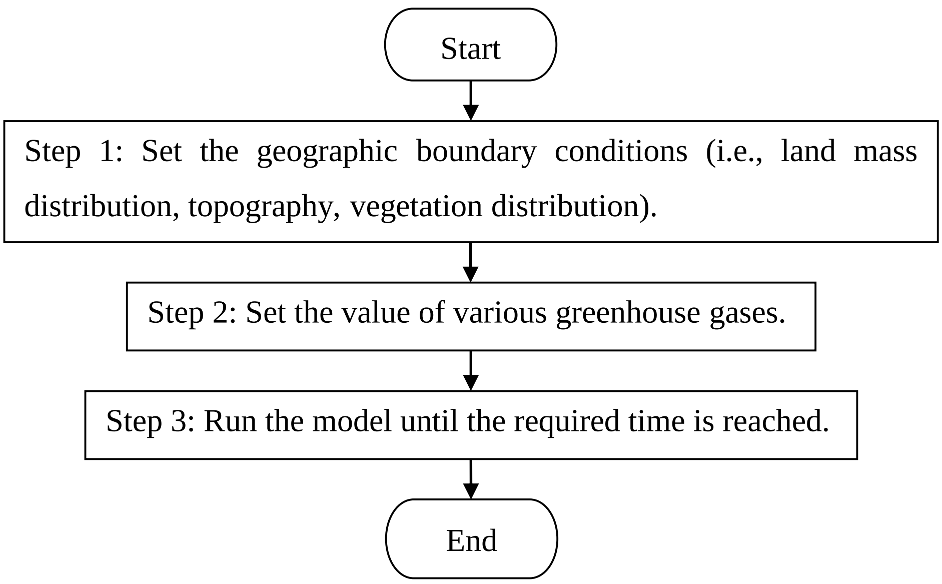

Figure 3.2 The steps for running the EdGCM (Columbia University, 2009).

3.2 The Data for the Educational Global Climate Model

The EdGCM model describes both seasonal and daily solar cycles in its temperature calculations. Cloud particles, aerosols, and radiatively important gases are explicitly incorporated into the radiation scheme. The data required for EdGCM are described in Table 3.1.

Table 3.1 The required conditions of EdGCM (Chandler et al., 2006).

Boundary Conditions	The boundary conditions are the description of the land-ocean distribution and the topography. The land surface cover is specified, including the locations and heights of continental ice sheets, the seasonal distribution of vegetation and the location and extent of lakes.
Initial Conditions	The initial conditions specify the starting temperature, pressure, winds, and humidity for every location in the atmosphere.
Climate Forcings	The climate forcings impact the results of the run more dramatically, such as greenhouse gases.
Climate Feedbacks	There are three feedback mechanisms that are illustrative of the process, and which are dominant mechanisms effecting global warming and cooling scenarios: the water vapor feedback, the cloud feedback, and the ice albedo feedback.
Climate Sensitivity	The sensitivity of the climate system to a forcing is most commonly expressed in terms of the global mean temperature change that would be expected after a time sufficiently long for both the atmosphere and the ocean to come to equilibrium with the change in climate forcing.

3.3 The Experiment Design

The EdGCM is designed for running 143-year predictions from the 1st January 1958 to 31st December 2100. Summary of the EdGCM runs are shown in Table 3.2 and Table 3.3. However, only the outputs of surface air temperature in April from 2010 to 2100 are used for predictability measurement in this research.

3.3.1 Case I : Pertubed CO_2

Table 3.2 Case I

Greenhouse gas	The Control Run (CTRL)	The Perturbed Runs (PERs)
Carbon Dioxide (CO_2)	314.9 ppm	PER1 : 1% increase of CO_2
		PER2 : 5% increase of CO_2
		PER3 : 10% increase of CO_2
		PER4 : 20% increase of CO_2
		PER5 : 50% increase of CO_2

Table 3.2 shows the initial concentration of carbon dioxide for the control run (CTRL) and the perturbed runs (PERs) for Case I.

3.3.2 Case II : Perturbed CO_2 and CH_4

Table 3.3 Case II

Greenhouse gas	The Control Run (CTRL)	The Perturbed Runs (PERs)
Carbon Dioxide (CO_2)	314.9 ppm	PER2 : 5% increase of CO_2
		PER6 : 5% increase of CH_4
Methane (CH_4)	1.2240 ppm	PER7 : 5% increase of CO_2 +5% increase of CH_4

Similarly, Table 3.3 shows the initial concentration of carbon dioxide and methane for the control run and the perturbed runs for Case II.

3.4 The Study Domain

The study domain covers Southeast Asian region between latitude 4° S to 28° N and longitude 95° E to 115° E as shown in Figure 3.3.

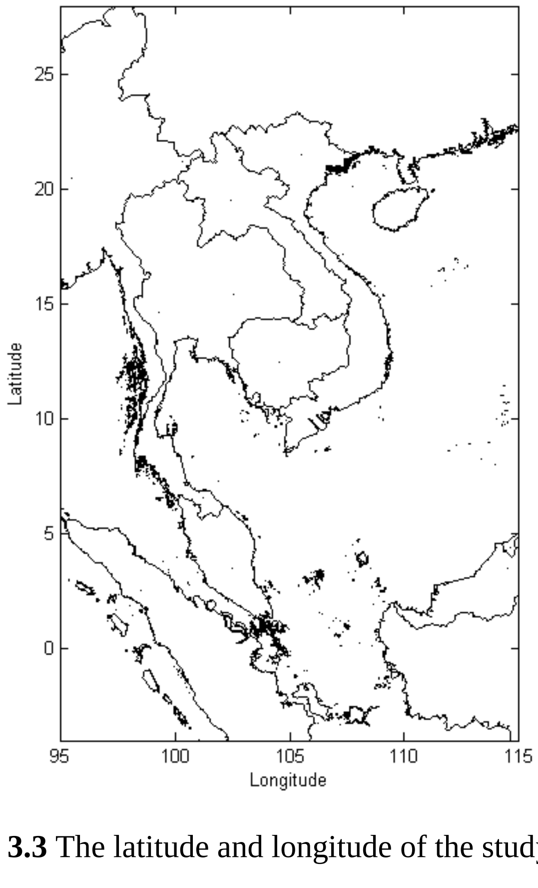

Figure 3.3 The latitude and longitude of the study domain.

3.5. The Modified Lyapunov Exponent

The predictability problem refers to those causes of uncertainty as model uncertainty and initial uncertainty. Most theoretical studies of atmospheric predictability tend to concentrate on the initial uncertainty and its propagation forwards in time through the integration of an otherwise deterministic flow model (Jifan, 1989). There are several methods that can be used to estimate model predictability. Most predictability measurement methods are based on the Lyapunov exponent (LE) with infinitesimal perturbation. LE provides a measure of the rate of convergence or divergence of nearby trajectories, which indicating the level of sensitivity of a system to initial condition (McCue, 2005). To establish a new predictability measurement method which associates the condition of the exponential rate to the growth rate of initial perturbation of dynamical models, the modified Lyapunov exponent (MoLE) is proposed as follows.

A time evolution is usually described by a dynamical system, which is given by the solution to differential equations in continuous time or difference equations in discrete time. Consider an *n*-dimensional continuous dynamical system. Assume that the evolution of the atmosphere is defined by the nonlinear differential equation (Baohua et al., 2006),

$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{F}(\mathbf{x}(t)) \tag{3.1}$$

where $\mathbf{x}(t) \in \mathbb{R}^n$ is the state space with respect to a continuous time *t*, $t \geq 0$ and **F** is an *n*-dimensional vector field. The solution of (3.1), $\mathbf{x}(t)$, will be called a reference solution with its initial condition $\mathbf{x}(0) = \mathbf{x}_0$.

Consider an *n*-dimensional discrete dynamical system described by the following form (Jifan, 1989)

$$\mathbf{x}(t+\Delta t) = \mathbf{F}(\mathbf{x}(t)), \tag{3.2}$$

where $\mathbf{x}(t) \in \mathbb{R}^n$ is the state space with respect to a discrete time *t*, $t \in \mathbb{N}$ and **F** is a continuously differentiable nonlinear function. Thus the $\mathbf{x}(t)$ value can be demonstrated based on initial value, $\mathbf{x}(0) = \mathbf{x}_0$.

Now, consider a one-dimensional map,

$$x(t+\Delta t) = f(x(t)), \tag{3.3}$$

For the separation between two points, the control state x_0 and the perturbed state $x_0 + \delta x_0$ where $\delta x_0 = \delta x(0)$ is the small initial perturbation added to x_0 at the initial time. Then at time *t*, the control and the perturbed states of the dynamical system will be evolved to $x_0(t)$ and $x_0(t) + \delta x(t)$, respectively, as shown in Figure 3.4.

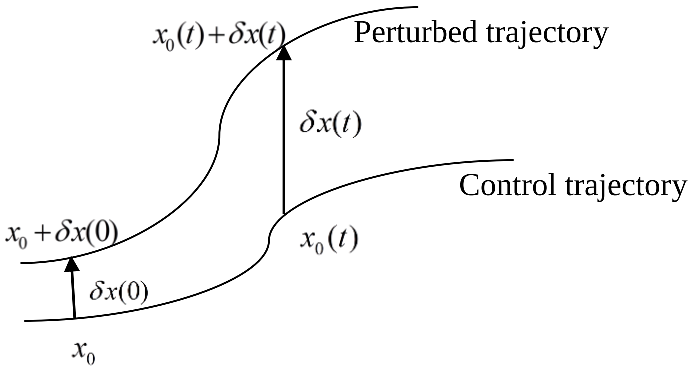

Figure 3.4 The schematic diagram of measuring error growth rate in the sense of LE.

Define the average surface air temperature $x_i(t),\ i=1,2,...,N$ as the state space of the dynamical system at time *t* where *N* is the total number of experiment data points. Then λ_i for $x_i(t)$ which is the separation rate of two trajectories at finite initial separation $\delta x_i(t),$ can be written as

$$\lambda_i(\delta x_i(t)) = \frac{1}{\Delta t}\ln\left(\frac{\|\delta x_i(t+\Delta t)\|}{\|\delta x_i(t)\|}\right) \qquad i = 1, 2, \ldots, N \qquad (3.4)$$

where $\delta x_i(t)$ is the distance between the control average surface air temperature $x_0(t)$ and the perturbed temperature $x_i(t) = x_0(t) + \delta x_i(t),$ with a suitable norm at time *t*. To establish the new measurement method namely modified Lyapunov exponent (MoLE), the weighted arithmetic mean of all trajectories $x_i(t)$ has been defined.

To find the weighted $w_i,\ i=1,2,\ldots,N$ which is associated with $x_i(t),\ i=1,2,...,N$ the approach is based on the work of Mishra (2004) which uses median as a weighted arithmetic mean of all experimental data. Let the median be a weighted arithmetic mean of x denoted by $med(x),$ the steps in this procedure are shown in Figure 3.5.

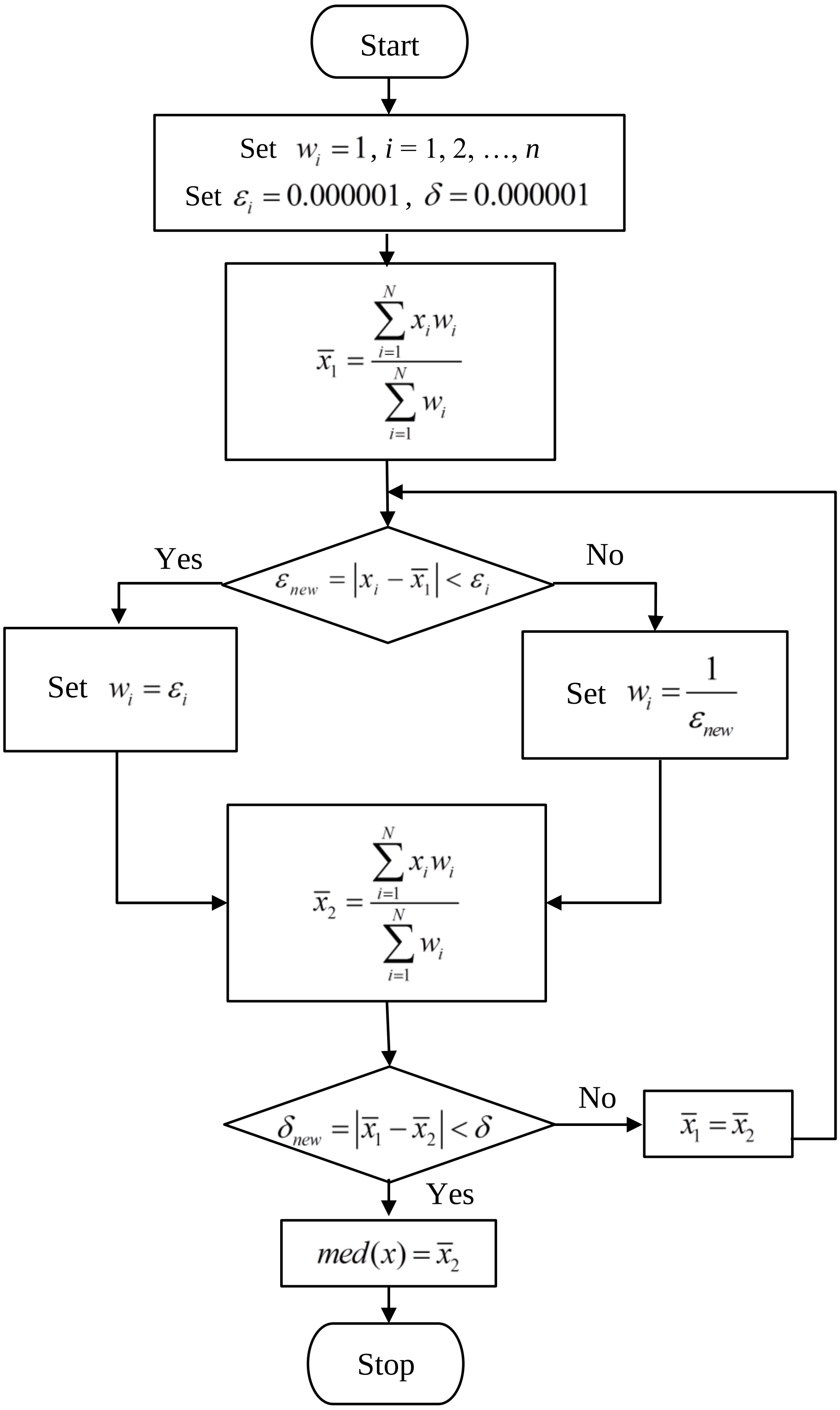

Figure 3.5 The steps to find the median from a weighted arithmetic mean calculation.

The weighted arithmetic mean of (3.4) over all of trajectories $x_i(t),\ i = 1, 2, ..., N$ in the phase space is the point of interest. Thus, for the state space of the dynamical system at time t of the point $x_i(t),\ i = 1, 2, ..., N$ which $w_i(t),\ i = 1, 2, ..., N$ exists, define MoLE at finite initial separation $\delta x_i(t)$ in the state space as

$$\lambda_i(w_i, \delta x_i(t)) = \frac{1}{\Delta t} \ln\left(\frac{\|\delta x_i(t+\Delta t)\|}{\|\delta x_i(t)\|} \right) \qquad i = 1, 2, \ldots, N \qquad (3.5)$$

where $\delta x_i(t)$ is the distance between the control average surface air temperature $x_0(t)$ and the perturbed temperature $x_i(t) = x_0(t) + \delta x_i(t),$ with a suitable norm at time *t*. Thus, MoLE can be used to measure the error growth rate in finite separation. The exponent λ_i depends not only on initial error but also weighted arithmetic mean of all experimental time series, which is different from the other types of LE. Moreover, median as weighted arithmetic mean lies at the middle part of the series and hence MoLE is not affected by the extreme values such as temperature in different region. The positive exponent indicates sensitive dependence on the initial conditions. The larger the exponent, the faster the error grows and the lower the predictability.