CHAPTER 3
METHODOLOGY

In order to investigate characteristic of active and break summer monsoon in climate change scenarios, the criteria of active and break of summer monsoon used by the Thai Meteorological Department are adopt as described in Section 2.5. The criteria for active monsoon are upper westerly wind is changed to easterly and lower wind is changed to westerly or southwesterly. The criteria for break monsoon are low pressure trough (Inter Tropical Convergence Zone-ITCZ) located over south China. Usually the first period of active monsoon is in June and the period of break monsoon is in July .

The single level primitive equation (SILEPE) model follows Krishnamutri (1986) is used in this research for ensemble forecast. The initial conditions are obtained from the Bjerknes Centre for Climate Research (BCCR), University of Bengen, Norway. The global climate model is Bergen Climate Model (BCM) Version 2.0 (BCCR-BCM2.0) from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model data set for the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change's 4th Assessment Report (IPCC). The resolution of the data is about 2.8×1.38 degree and collected to yearly tar file which contain several daily NetCDF format files. Finally, perturbed initial conditions for ensemble forecast are generated by the singular vector method.

3.1 Description of the Initial Data of the Test Case for the Model

The first step in this research is to test the performance of the single level primitive equation (SILEPE) model that is used in this study. The cases for the experiments of testing the model (Sukawat, 2012) for an active monsoon case is 15 May 2000 (Case A) and for a break monsoon case is 1 July 2000 (Case B).

The data for the above cases are obtained from NCEP/NCAR reanalysis (NOAA National Center for Environmental Prediction, 1996) of 1 degree grid resolution (about 100 km) and there are data for every 6 hour, with 17 pressure levels.

3.2 Description of the Initial Data of the Test Case for Singular Method

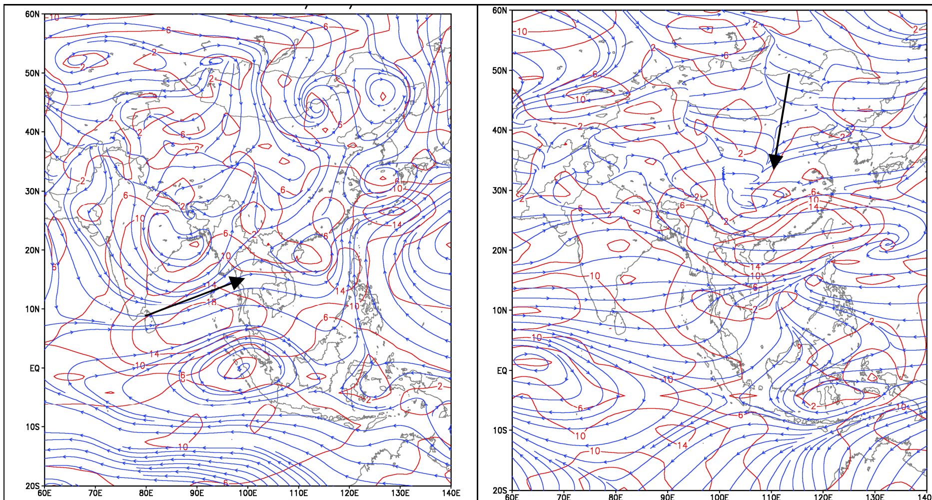
The data obtained from the Bjerknes Centre for Climate Research (BCCR) at University of Bergen, Norway under the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset for preparing the Fourth Asssessment Report (AR4) of the Intergovernmental Panel on Climate Change (Intergovernmental Panel on Climate Change-IPCC, 2009) are selected for testing the generation of initial perturbation in the singular vector process. The Special Report on Emissions Scenario (SRES) data and Non-SRES for the Atmospheric Environment are shown in Table 3.1 (NOAA National Center for Environmental Prediction, 1996). Each storyline represents different demographic, social, economic, technological, and environmental developments. The scenarios encompass different future developments that might influence greenhouse gas (GHG) sources and sinks, such as alternative structures of energy systems and land-use changes.

Table 3.1 The Special Report on Emissions Scenario (SRES) data and Non-SRES for the Atmospheric Environment (NOAA National Center for Environmental Prediction, 1996).

SRES	Description
A1	Assume economic growth quickly, population growth decrease and more new technologies in the future. Unbalancing of economic and cultural in per capital income in different regions. Emphasize wealth people than environment quality.
A2	Following A1 storyline but change a service and information economic structure quickly, reduce in material intensity, and using clean resource technologies.
Non-SRES	**Description**
COMMIT	An idealised scenario in which the atmospheric burdens of long-lived greenhouse gasses are held fixed at AD2000 levels.

3.3 Experiment Cases

The experiment cases (Table 3.1) are selected as representative of an active and a break of the summer monsoon that impact Thailand (Sukawat, 2012). The 850 winds of the active and break of the summer monsoon from the BCCR-BCM2.0 model database are plotted as shown in Figure 3.1.



(a) 12 May 2086, A2-Scenario

(b) 22 July 2086, A2-Scenario

Figure 3.1 Wind at 850 hPa (a) active summer monsoon and (b) summer monsoon break.

Table 3.2 The experiment cases.

Case		Model Scenario	Event	Initial Condition
Perturbation	Control Run			
1	CTL1	A2	Active	12 May 2086
2	CTL2	A2	Break	22 July 2086
3	CTL3	COMMIT	Active	19 May 2086
4	CTL4	COMMIT	Break	18 June 2086

The experiment cases for testing SILEPE model are shown in Table 3.3.

Table 3.3 The experiment setting for testing the performance of SILEPE model**.**

Model Domain	lat: 40°S to 80°N, long: 180°W to 180°E
Model Resolution	$\Delta x = \Delta y = 1^{\circ}$, $\Delta t = 60\ s$.
Initial Condition	NCEP data reanalysis (follow the cases in Table 3.2), 850 hPa Case A 15 May 2000 00UTC Case B 01 July 2000 00UTC
Boundary Condition	Cyclic in the west-east boundary Open in the north-south boundary
Forecast Time	4 days

3.4 Domain Area

3.4.1 Domain for SILEPE Model

The SILEPE model is run using the BCCR-BCM2.0 output as initial conditions. The domain covers 180°W to 180°E and 40°S to 60°N to satisfy the east-west cyclic boundary and to reduce the problem at the north and south boundaries (Figure 3.2).

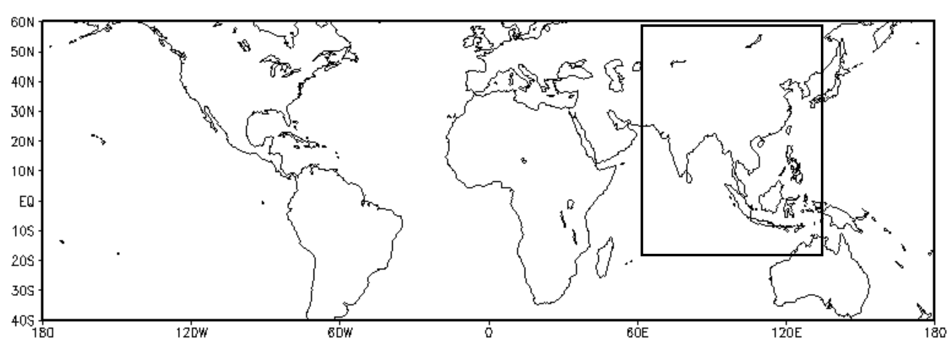


Figure 3.2 Domain of study for SILEPE.

3.4.2 Study Domain

Domain of the model is divided into 81x81 grids, covering 60°E to 140°E and 20°N to 60°N as shown in Figure 3.3. The horizontal resolution of each cell is $\Delta x = \Delta y = 1^{\circ}$.

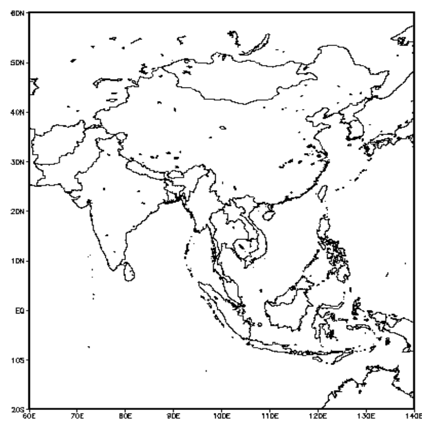


Figure 3.3 Domain of study.

The steps for preparing the data set for geopotential (*zg*), zonal wind component (*ua*) and meridinal wind component (*va*) from the WCRP CMIP3 (University Corporation for Atmospheric Research-UCAR, 2004) multi-model database are shown in Figure 3.4.

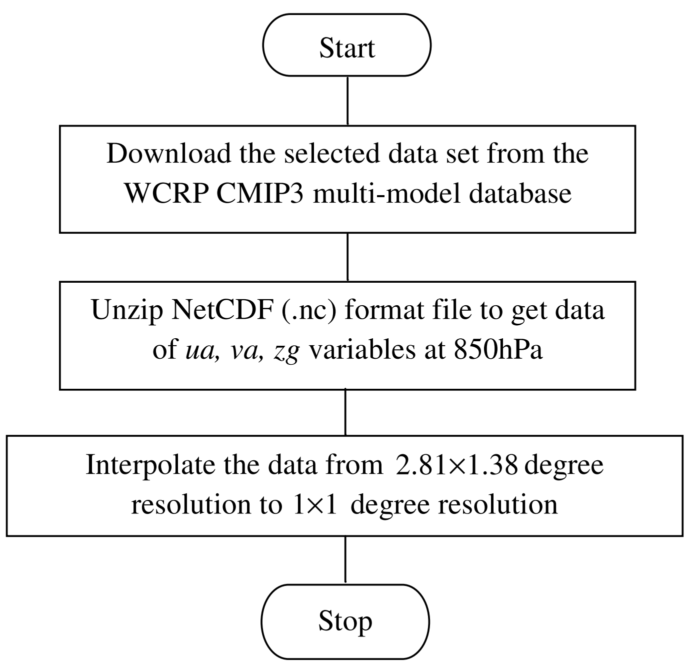


Figure 3.4 The steps for preparing the data set from the WCRP CMIP3 multi-model database.

3.5 The Single Level Primitive Equation (SILEPE) Model

The SILEPE model (Krishnamutri, 1986) is based on the shallow water equations. Basically, shallow water equations are defined as

$$\frac{du}{dt} - fv + g\frac{\partial \phi}{\partial x} = 0 \qquad (3.1)$$

$$\frac{dv}{dt} + fu + g\frac{\partial \phi}{\partial y} = 0 \qquad (3.2)$$

$$\frac{d\phi}{dt} + \phi\left(\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y}\right) = 0 \qquad (3.3)$$

The total time derivative is given by $\frac{d}{dt} = \frac{\partial u}{\partial t} + u\frac{\partial}{\partial x} + v\frac{\partial}{\partial y}$.

Equations (3.1) – (3.3) can be rewritten as,

$$\frac{du}{dt} = -g\frac{\partial \phi}{\partial x} + fv \qquad (3.4)$$

$$\frac{dv}{dt} = -g\frac{\partial \phi}{\partial y} - fu \qquad (3.5)$$

$$\frac{d\phi}{dt} = -\phi\left(\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y}\right) \qquad (3.6)$$

where u is wind velocity in the x directions (m/s)

v is wind velocity in the y directions (m/s)

ϕ is geopotential height (m)

g is acceleration due to gravity (m/s^2)

f is Coriolis parameter which is given by $f = 2\Omega \sin\theta$ (Ω is the angular velocity of the earth, θ is the latitude).

This model uses the zonal and meridional components of the wind field and the height field as the predicted variables. The advection term is calculated by a semi– Lagrangian approach. The Matsuno time scheme is applied to time integration. Generally, the computation of the pressure gradient force term in the momentum equations and the divergence term in the continuity equation are approximated by centered differencing (Krishnamutri, 1986). The processing of model is shown in Figure 3.5.

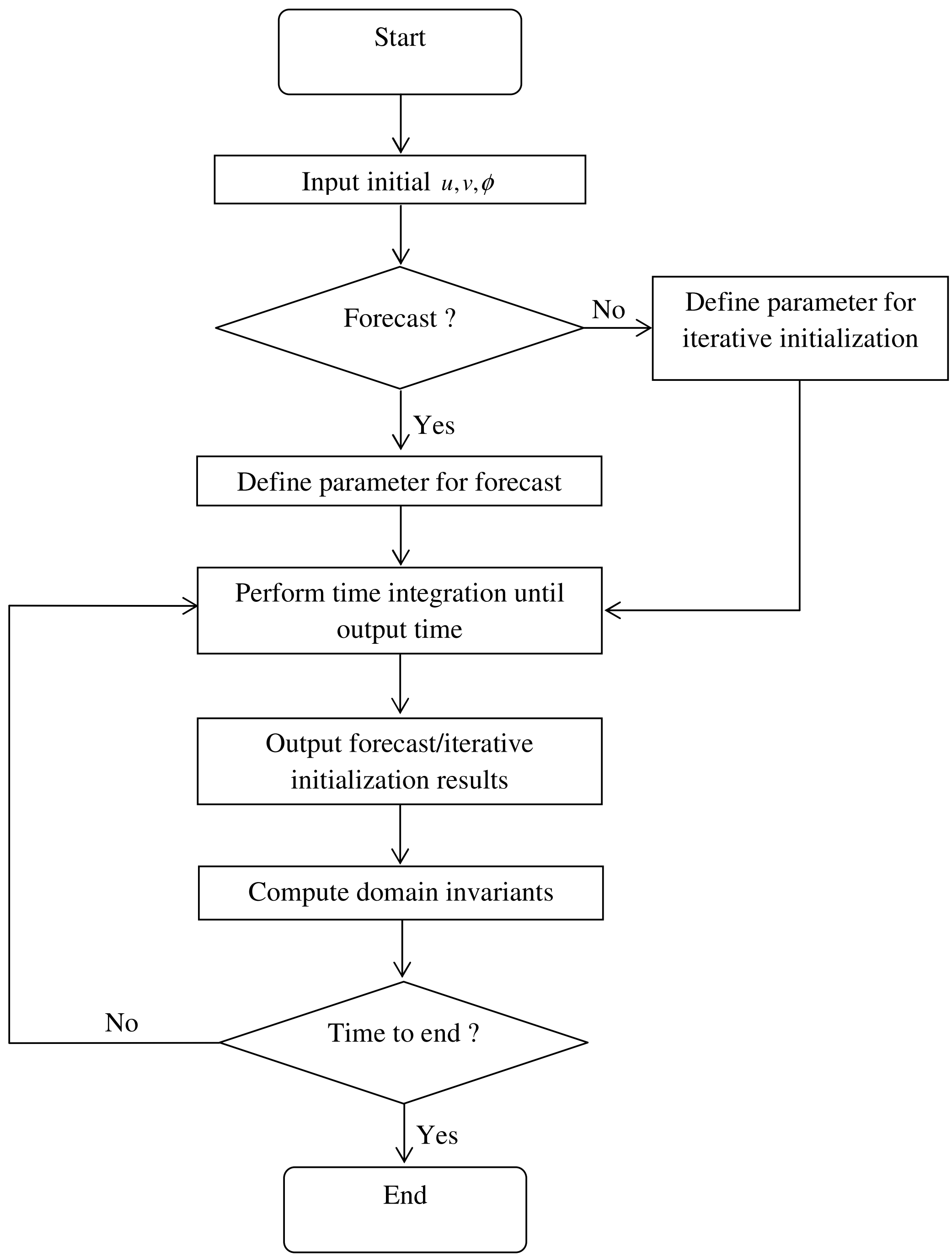


Figure 3.5 Flow chart showing processes in SILEPE model (Krishnamutri, 1986).

3.6 Singular Vector of the SILEPE Model for Initial Condition Generation

The singular vector method as explained by Kalnay (2003) and Molteni et al. (1996) is applied to the SILEPE model to generate initial ensemble members. Generally, ensemble members are made by adding to the initial condition (observation data) small perturbations that are produced by singular vector. Tangent linear model is a linearized version of the full (non-linear) operational forecast model. The adjoint which is selected to calculate the tangent linear model is based on the singular vector. This concept is applied to SILEPE model. In this research, a linear version of the SILEPE model is used instead of the tangent linear model. Linearization of the SILEPE model is done as follows.

3.6.1 Linearization of SILEPE model

From the nonlinear model, define $\left(\bar{\ }\right)$ as the area average over the model domain. Assume the flow is non-divergent in Eq. (3.3), $\left(\frac{\partial u}{\partial x}+\frac{\partial v}{\partial y}\right)=0$ which implies $\frac{d\phi}{dt}=0.$ Thus, the linear model (LM) will be

$$\frac{\partial u}{\partial t}+\bar{u}\frac{\partial u}{\partial x}+\bar{v}\frac{\partial u}{\partial y}-fv+g\left(\frac{\partial\bar{\phi}}{\partial x}\right)=0 \qquad (3.7)$$

$$\frac{\partial v}{\partial t}+\bar{u}\frac{\partial v}{\partial x}+\bar{v}\frac{\partial v}{\partial y}+fu+g\left(\frac{\partial\bar{\phi}}{\partial y}\right)=0 \qquad (3.8)$$

The above two equations can be written as

$$\frac{\partial u}{\partial t}=-\bar{u}\frac{\partial u}{\partial x}-\bar{v}\frac{\partial u}{\partial y}+fv \qquad (3.9)$$

$$\frac{\partial v}{\partial t}=-fu-\bar{u}\frac{\partial v}{\partial x}-\bar{v}\frac{\partial v}{\partial y} \qquad (3.10)$$

Rearrange Eq. (3.9) and Eq. (3.10) as

$$\begin{bmatrix} \frac{\partial u}{\partial t} \\ \frac{\partial v}{\partial t} \end{bmatrix} = \begin{bmatrix} -\bar{u}\frac{\partial}{\partial x} - \bar{v}\frac{\partial}{\partial y} & f \\ -f & -\bar{u}\frac{\partial}{\partial x} - \bar{v}\frac{\partial}{\partial y} \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} \tag{3.11}$$

The linear model (LM) is defined such that

$$\mathbf{L} = \begin{bmatrix} -\bar{u}\frac{\partial}{\partial x} - \bar{v}\frac{\partial}{\partial y} & f \\ -f & -\bar{u}\frac{\partial}{\partial x} - \bar{v}\frac{\partial}{\partial y} \end{bmatrix} \tag{3.12}$$

where $\mathbf{L}$ is the linear model.

So the LM evolves a perturbation in time

$$\mathbf{y(t)} = \mathbf{L}(t_0, t)\mathbf{y}(t_0) \tag{3.13}$$

where $\mathbf{y}(t_0)$ is the perturbation state at the initial time $t = 0$.

$\mathbf{y}(t)$ is the perturbation state at time t.

3.6.2 The Adjoint of Linear Model

The adjoint linear model is the transpose of the linear model. It is defined with respect to the inner product of two arbitrary vectors.

$$\langle \mathbf{L}u, v \rangle = \langle u, \mathbf{L}^{\mathbf{T}} v \rangle \tag{3.14}$$

where u is wind speed in x-direction.

v is wind speed in y-direction.

$\mathbf{L}^{\mathbf{T}}$ is the adjoint LM.

So that the adjoint linear model is

$$\mathbf{L^T} = \begin{bmatrix} -\bar{u}\frac{\partial}{\partial x} - \bar{v}\frac{\partial}{\partial y} & f \\ -f & -\bar{u}\frac{\partial}{\partial x} - \bar{v}\frac{\partial}{\partial y} \end{bmatrix} \tag{3.15}$$

3.6.3 Singular Vector

Singular vectors (SVs) method is explained according to Kalnay (2003). For an interval (t_0, t_1), the LM is a matrix that when applied to a small initial perturbation $\mathbf{y}(t_0)$ produces the final perturbation $\mathbf{y}(t_1)$

$$\mathbf{y}(t_1) = \mathbf{L}(t_0, t_1)\mathbf{y}(t_0) \tag{3.16a}$$

Applying the adjoint of linear model to a small final perturbation $\mathbf{y}(t_1)$ produces the initial perturbation $\mathbf{y}(t_0)$

$$\mathbf{y}(t_0) = \mathbf{L^T}(t_1, t_0)\mathbf{y}(t_1) \tag{3.16b}$$

Singular value decomposition theory indicates that for any matrix $\mathbf{L}$ there exist two orthogonal matrices $\mathbf{A}, \mathbf{\Lambda}$ such that

$$\mathbf{A^T L \Lambda = S} \tag{3.17}$$

where $\mathbf{S} = \begin{bmatrix} \sigma_1 & 0 \\ 0 & \sigma_2 \end{bmatrix}$ and $\mathbf{AA}^T = \mathbf{I}$, $\mathbf{\Lambda\Lambda}^T = \mathbf{I}$

$\mathbf{S}$ is a diagonal matrix whose σ_i elements are the singular values of $\mathbf{L}$.

$\mathbf{I}$ is the identity matrix.

Left multiply Eq.(3.17) by $\mathbf{A}$, to get

$$\mathbf{L\Lambda = AS} \tag{3.18}$$

$$\mathbf{L}(\boldsymbol{\eta}_1, \boldsymbol{\eta}_2) = (\sigma_1\boldsymbol{\zeta}_1, \sigma_2\boldsymbol{\zeta}_2) \tag{3.19}$$

where $\boldsymbol{\eta}_\mathbf{i}$ are the columns of $\mathbf{\Lambda}$

$\boldsymbol{\zeta}_\mathbf{i}$ are the columns of $\mathbf{A}$.

$i = 1, 2$ represent index of vector

This implies that

$$\mathbf{L}\boldsymbol{\eta}_i = \sigma_i \boldsymbol{\zeta}_i \tag{3.20}$$

Eq. (3.20) defines $\boldsymbol{\eta}_i s$ as the right singular vectors of $\mathbf{L}$, hereafter referred to as initial singular vectors, since they are valid at the beginning of optimization interval over which $\mathbf{L}$ is defined.

Right multiply Eq. (3.17) by $\mathbf{\Lambda^T}$ and transposing

$$\mathbf{L^T A = \Lambda S} \tag{3.21}$$

$$\mathbf{L}^T(\boldsymbol{\zeta}_1, \boldsymbol{\zeta}_2) = (\sigma_1 \boldsymbol{\eta}_1, \sigma_2 \boldsymbol{\eta}_2) \tag{3.22}$$

So that

$$\mathbf{L}^T \boldsymbol{\zeta}_i = \sigma_i \boldsymbol{\eta}_i \tag{3.23}$$

The $\boldsymbol{\zeta}_i s$ are the left singular vectors of $\mathbf{L}$ and will be referred to as final (or evolved) singular vectors, since they correspond to the end of the interval of optimization.

From Eq. (3.20) multiply by $\mathbf{L}^T$

$$\mathbf{L}^T \mathbf{L}\boldsymbol{\eta}_i = \sigma_i \mathbf{L}^T \boldsymbol{\zeta}_i \tag{3.24}$$

From Eq. (3.23)

$$\mathbf{L}^T \mathbf{L}\boldsymbol{\eta}_i = \sigma_i (\sigma_i \boldsymbol{\eta}_i) \tag{3.25}$$

$$\mathbf{L}^T \mathbf{L}\boldsymbol{\eta}_i = \sigma_i^2 \boldsymbol{\eta}_i \tag{3.26}$$

Consequently, $\mathbf{L}$ is multiplied into Eq. (3.23)

$$\mathbf{L}\mathbf{L}^T \boldsymbol{\zeta}_i = \sigma_i \mathbf{L}\boldsymbol{\eta}_i \tag{3.27}$$

From Eq. (3.20)

$$\mathbf{L}\mathbf{L}^T \boldsymbol{\zeta}_i = \sigma_i (\sigma_i \boldsymbol{\zeta}_i) = \sigma_i^2 \boldsymbol{\zeta}_i^2 \tag{3.28}$$

Therefore, the initial singular vectors can be obtained as the eigenvectors of $\mathbf{L}^T\mathbf{L}$, the final singular vectors can be obtained as the eigenvectors of $\mathbf{L}\mathbf{L}^T$ and a normal matrix whose eigenvalues are the squares of the singular values.

Basically, trajectories are

$$\mathbf{y}(t_0) = \sum_{i=1}^{n} < \mathbf{y}(t_0), \eta_i > \eta_i \tag{3.29a}$$

$$\mathbf{y}(t_1) = \sum_{i=1}^{n} < \mathbf{y}(t_1), \zeta_i > \zeta_i \tag{3.29b}$$

From Eq. (3.16a) and Eq. (3.29a)

$$\begin{aligned} \mathbf{y}(t_1) &= \mathbf{L}(t_0, t_1) \sum_{i=1}^{n} < \mathbf{y}(t_0), \boldsymbol{\eta}_i > \boldsymbol{\eta}_i \\ &= \sum_{i=1}^{n} < \mathbf{y}(t_0), \boldsymbol{\eta}_i > \mathbf{L}(t_0, t_1) \boldsymbol{\eta}_i \end{aligned} \tag{3.30}$$

Since $\sum_{i=1}^{n} < \mathbf{y}(t_0), \boldsymbol{\eta}_i >$ is a scalar, thus $\mathbf{y}(t_1) = \sum_{i=1}^{n} < \mathbf{y}(t_0), \boldsymbol{\eta}_i > \sigma_i \boldsymbol{\zeta}_i$

Take inner product by $\boldsymbol{\zeta}_i$

$$< \mathbf{y}(t_1), \boldsymbol{\zeta}_i > = \sigma_i < \mathbf{y}(t_0), \boldsymbol{\eta}_i > \tag{3.31}$$

This indicates that by applying the linear model $\mathbf{L}$, each initial vector $\boldsymbol{\eta}_i$ component will be stretched by an amount equal to the singular value σ_i and the direction will be rotated to that of the evolved vector $\boldsymbol{\zeta}_i$.

Consequently, from Eq. (3.29b) and Eq. (3.16b)

$$\begin{aligned} \mathbf{y}(t_0) &= \mathbf{L}^T(t_0, t_1) \mathbf{y}(t_1) \\ &= \mathbf{L}^T(t_0, t_1) \sum_{i=1}^{n} < \mathbf{y}(t_1), \boldsymbol{\zeta}_i > \boldsymbol{\zeta}_i \end{aligned} \tag{3.32}$$

Since $\sum_{i=1}^{n} < \mathbf{y}(t_1), \boldsymbol{\zeta}_i >$ is a scalar, so

$$\mathbf{y}(t_0) = \sum_{i=1}^{n} < \mathbf{y}(t_1), \boldsymbol{\zeta}_i > \mathbf{L}^T(t_0, t_1)\boldsymbol{\zeta}_i \tag{3.33}$$

$$\mathbf{y}(t_0) = \sum_{i=1}^{n} < \mathbf{y}(t_1), \boldsymbol{\zeta}_i > \sigma_i \boldsymbol{\eta}_i \tag{3.34}$$

Take inner product by $\boldsymbol{\eta}_i$ to get

$$< \mathbf{y}(t_0), \boldsymbol{\eta}_i > = \sigma_i < \mathbf{y}(t_1), \boldsymbol{\zeta}_i > \tag{3.35}$$

This indicates that by applying the adjoint linear model $\mathbf{L}^T$, each initial vector $\boldsymbol{\eta}_i$ component will be stretched by an amount equal to the singular value σ_i and the direction will be rotated to that of the evolved vector $\boldsymbol{\zeta}_i$.

Applying linear and adjoint linear model into singular vectors

$$< \mathbf{y}(t_1)_n, \boldsymbol{\zeta}_i > = \sigma_i < \mathbf{y}(t_0)_n, \boldsymbol{\eta}_i > \tag{3.36}$$

$$< \mathbf{y}(t_0)_{n+1}, \boldsymbol{\eta}_i > = \sigma_i < \mathbf{y}(t_1)_n, \boldsymbol{\zeta}_i > \tag{3.37}$$

where subscript n represents initial state and $n+1$ represents final state of transformation.

This process is recursived until the difference between the norm of the perturbation at the initial state $\|\mathbf{y}(\mathbf{t_0})\|_n$ and the final state $\|\mathbf{y}(\mathbf{t_0})\|_{n+1}$ is smaller than ε.

$$\left| \|\mathbf{y}(\mathbf{t_0})\|_n - \|\mathbf{y}(\mathbf{t_0})\|_{n+1} \right| < \varepsilon \tag{3.38}$$

where ε is set to 1×10^{-2} ms^{-1}.

In this research the norm of vector is defined as

$$\|\mathbf{y}(\mathbf{t_0})\| = \sqrt{|\mathbf{u}|^2 + |\mathbf{v}|^2}. \tag{3.39}$$

This indicates that applying $\mathbf{LL}^T$ is running linear model forward in time, and then the adjoint backward in time; the first initial singular vectors $\boldsymbol{\eta}_i$ will grow by factor σ_i^2.

The maximum perturbation norm of perturbation is added to the initial condition to generate the new initial conditions. The steps for generation of a perturbation are as follows.

1. Select the area to be perturbed from the data of BCCR-BCM2.0 model. The area perturbed is located at latitude 5^{o}S to 20^{o}N and longitude 85^{o}E to 110^{o}E that is 25×25 grid point.

2. Formulate the linear model Eq. 3.12 and adjoint linear model Eq. 3.15 for $\mathbf{L}\mathbf{L}^{T}$ and $\mathbf{L}^{T}\mathbf{L}$.

3. Find singular vector and singular value of $\mathbf{L}\mathbf{L}^{T}$ and $\mathbf{L}^{T}\mathbf{L}$ using initial data from the first step.

4. Define an initial perturbation $y(t_0)$ of u and v which satisfies $\sqrt{u^2+v^2} = 1$ ms^{-1} in the area of the first step.

5. For each grid point, generate a new perturbation by the singular vector method Eq. 3.36 and Eq. 3.37, using the initial perturbation from Step 4 and singular vector and singular value from Step 3.

6. Verify the norm of the transformed perturbation follow the condition in Eq. 3.38 for each grid point. If the condition is not satisfied with Eq. 3.38 the perturbation is normalized as initial perturbation. Repeat Step 5 until Eq.3.38 is satisfied. Otherwise, the final perturbation is obtained.

7. Finally, adding and subtracting the final perturbation to the in initial data in Step 1 called positive perturbation (+PRT) and negative perturbation (-PRT), respectively. The final perturbation is obtained by multiply with the scale factor which is 1.05 of the initial perturbation value.

The data obtained from the data of BCCR_BCM2.0 model are used as the initial condition for control runs. Perturbed initial conditions for ensemble forecasts are generated from the data of BCCR_BCM2.0 model using the singular vector method. A flow diagram of the singular vector method is shown in Figure 3.6.

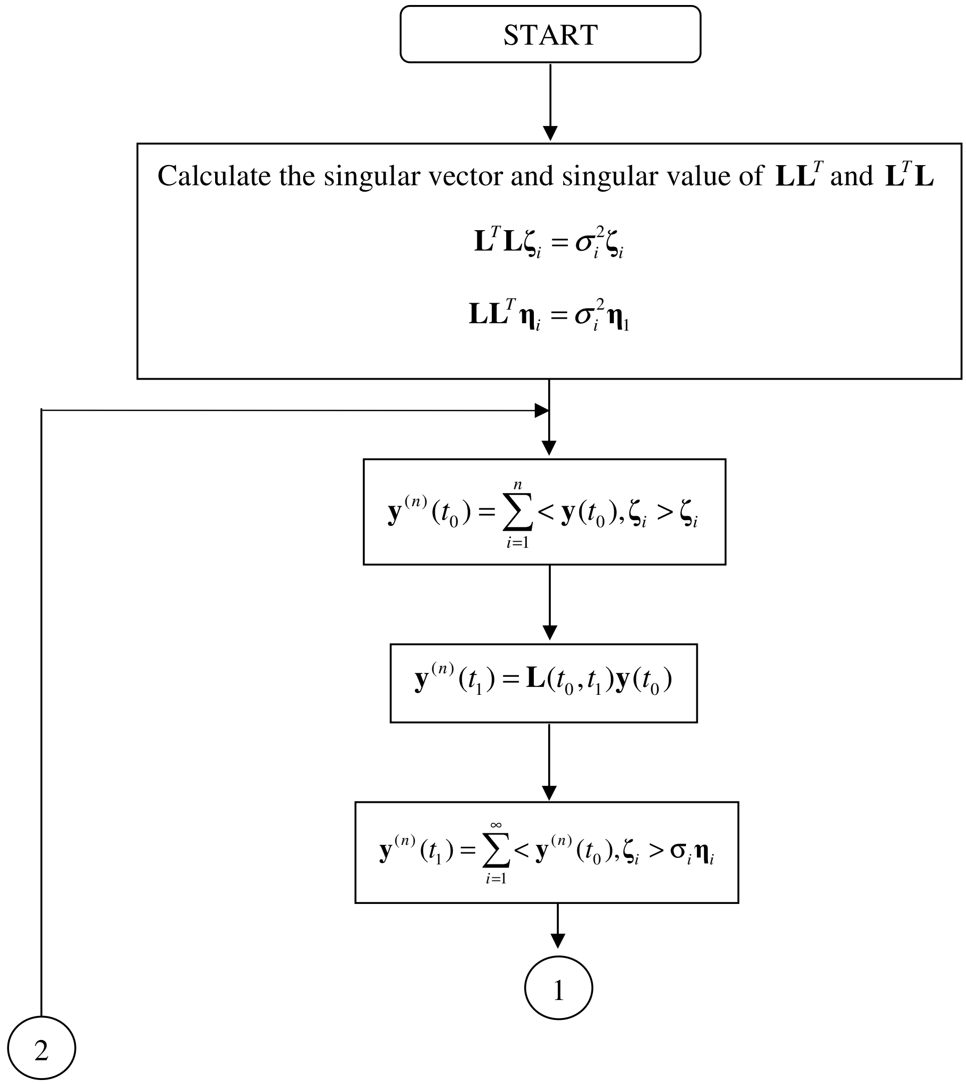


Figure 3.6 The steps of singular vector calculation.

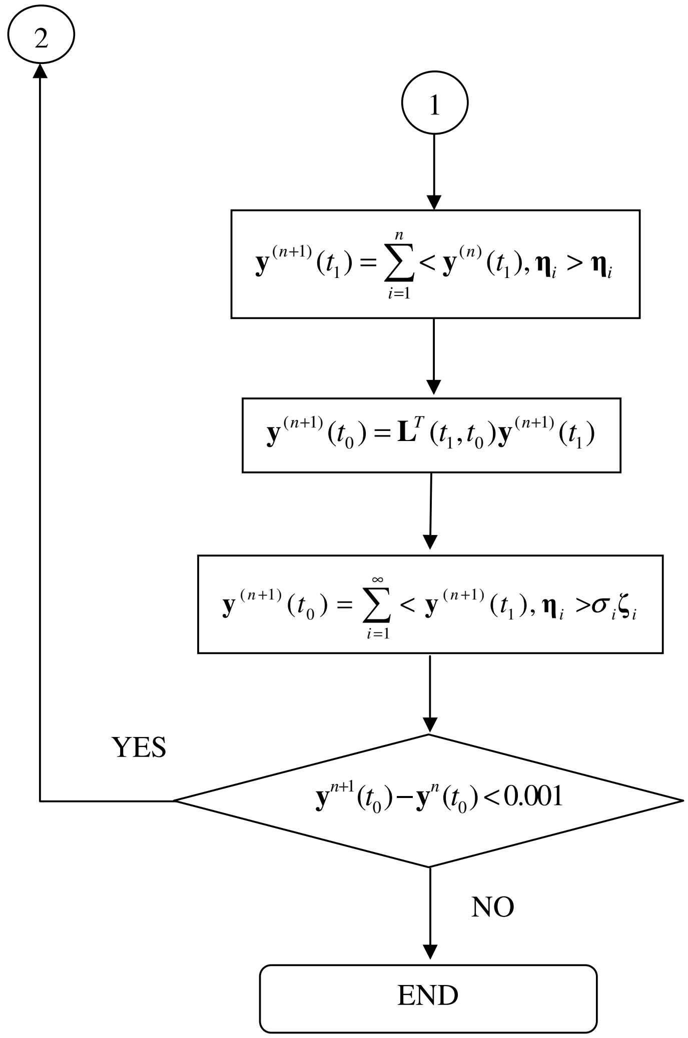


Figure 3.6 (Cont.)

3.7 Ensemble Forecasting from Singular Vector

After obtaining the singular vectors from the singular vector method, the initial conditions from A2 and COMMIT scenarios are perturbed by adding and subtracting singular vectors over the study domain. The SILEPE is run for 4-day forecast to generate 50 ensemble members.

3.8 Sensitivity Analysis

3.8.1 Directional Mean and Circular Variance

The directional mean shows the mean direction of the set of vectors and is concerned with direction but not the length of vectors, vectors can be simplified to 1 unit in length (unit vectors). Each vector shows a direction in reference to the origin. The result of the vector addition is defined as the directional mean of the set of the vector and can be derived from the following trigonometric relation (Wong and Lee, 2005)

$$tan\,\theta_R = \frac{v}{u} \tag{3.40}$$

where v is wind component in y direction

u is wind component in x direction, i.e. $\mathbf{v} = (u, v)$

There are n vectors $\mathbf{v}$ and the angle of the vector $\mathbf{v}$ from the x-axis is θ_v, the resultant vector forms the angle θ_R counter-clockwise from the x-axis and each vector is of unit length,

$$tan\theta_R = \frac{\sum sin\theta_v}{\sum cos\theta_v} \tag{3.41}$$

where $tan\theta_R$ is the tangent of the resultant vector. The directional mean is the angle of the resultant vector θ_R that is the average direction of the set of vectors. A measure showing the variation or dispersion among the vectors is necessary for the directional mean, this measure is the circular variance. The length of the resultant vector is

$$Le = \sqrt{\left(\sum sin\theta_v\right)^2 + \left(\sum cos\theta_v\right)^2}\ . \tag{3.42}$$

Circular variance, S_v

$$S_v = 1 - \left(\frac{Le}{n}\right) \tag{3.43}$$

where n is the number of vectors. S_v ranges from 0 to 1. When $S_v = 0$ means all vectors have the same direction. $S_v = 1$ implies all vectors are in opposite direction.

3.8.2 Ensemble Probability Forecast

The relationship of ensemble forecasts to A2 and COMMIT over Southeast Asia can also be expressed in terms of ensemble forecast probability. The ensemble forecast probability is calculated as the fraction of the number of ensemble members that is in the specified error range, with all ensemble member (Saelao, 2011). It can be written as

$$P_i(E) = \frac{n_i(E)}{n(T)} \times 100 \tag{3.44}$$

where

E is the error range (difference between ensemble member and A2 or COMMIT).

$P_i(E)$ is the probability of E at point *i*.

$n_i(E)$ is the number of ensemble member that satisfies E at the grid point *i*.

$n(T)$ is the total number of ensemble number.

Ensemble forecast probability is a method to show probability of ensemble member that satisfies the event *E* each the grid point.

3.9 Relative Skill Score (RSS)

A statistic use to verify error from the model, relative skill score is discussed in this section. The ensemble mean is calculated from

$$\overline{F} = \frac{1}{N}\sum_{i=1}^{N} F_i \tag{3.45}$$

where F_i is the i^{th} ensemble member.

N is the total of number of ensemble member.

The ensembles mean error (*E*) when verified with the analysis is

$$E = \left|\overline{F} - A\right|. \tag{3.46}$$

The relative skill score (RSS) is an index statistic score that shows relation between analysis error and model error. Control and ensemble mean are selected to calculate RSS. However, this score result depends on member which is chosen. The relative skill score (RSS) is defined as (Kevin and Johnny, 1999)

$$RSS = \frac{\mathrm{E_{CONTROL}} - \mathrm{E_{ENSEMBLE}}}{\mathrm{E_{CONTROL}} + \mathrm{E_{ENSEMBLE}}} \times 100\% \tag{3.47}$$

where $\mathrm{E_{CONTROL}}$ is the error of control run, $\mathrm{E_{ENSEMBLE}}$ is the average error of the ensemble mean.