ESTIMATION OF POTENTIAL EVAPOTRANSPIRATION UNDER CLIMATE CHANGE USING DATA MINING: A CASE STUDY OF THAILAND

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Thesis
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M.Sc. (APPROPRIATE TECHNOLOGY FOR RESOURCES AND ENVIRONMENTAL DEVELOPMENT)

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Abstract

The objective of this study was to estimate Potential Evapotranspiration (ET_o) under climate change impact using Data Mining technique. The study was based on climate projection under 3 different atmospheric concentrations of carbon dioxide (CO_2), which was the main greenhouse gas that cause global warming; 360 ppm (climate scenario 1: baseline condition), 540 ppm (climate scenario 2: medium term future) and 720 ppm (climate scenario 3: long term future). Climatic data from the Meteorological Department of Thailand during 1980 to 1989 was used to create on Artificial Neural Networks model. 118,742 climatic data observations were put into the ANNs model. The variables in monthly time step, which were included into model run consist of: maximum temperature, minimum temperature, precipitation, maximum wind speed, solar radiation, relative humidity and evapotranspiration.

It was found that the best ANNs architectural layer is six, thirty four, and one neuron (6-34-1) in the input, hidden, and output layers with 2000 antennary for learning time and with 0.1 and 0.1 learning rate and momentum.

Results showed a decrease trend of ET_o in the medium term future under future climate conditions; when CO_2 concentration is 540 ppm (climate scenario 2) ET_o will decrease approximately 26 % in January, 5 % in February, 2 % in March, 12 % in April, 18 % in May, 7 % in June, 12 % in July, 9 % in August, 17 % in September, 9 % in October, 8 % in November and 13 % in December.

In the longer term future, climate conditions under CO_2 concentration 720 ppm (climate scenario 3), analysis result showed fluctuations of ET_o over the year when compared to the baseline period. ET_o will increase by up to 14 % in January, 2 % in February, 8 % in March, 5 % in May, 15 % in June, but ET_o will decrease 2 % in April, 3 % in July, 5 % in August, 8 % in September, 5 % in October, and 8 % in December**.**

After using coefficient to compare ET from paddy fields in the medium term future under future climate condition when CO_2 concentration is 540 ppm (climate scenario 2) ET_o will decrease about 18 % in May, 7 % in June, 12 % in July, 9 % in August, 17 % in September. But under climate condition when CO_2 concentration is 720 ppm (climate scenario 3), ET from paddy fields will increase by up 6 % in the first and 14 % in the second month while in the third to the fifth months ET from paddy fields will decrease by 3 %, 5 %, and 8 % on respectively.

KEY WORDS: POTENTIAL EVAPOTRANSPIRATION/ CLIMATE CHANGE/ DATA MINING/ ARTIFICIAL NEURAL NETWORK

73 pp.

การคาดการณ์ศักย์การคายระเหยของพืชอ้างอิง (ET_o) จากการเปลี่ยนแปลงสภาพภูมิอากาศโลก โดยการประยุกต์ใช้เทคนิคการทำเหมืองข้อมูล (Data Mining): กรณีศึกษาประเทศไทย

(ESTIMATION OF POTENTIAL EVAPOTRANSPIRATION UNDER CLIMATE CHANGE USING DATA MINING: A CASE STUDY OF THAILAND)

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คณะกรรมการควบคุมวิทยานิพนธ์: กัมปนาท ภักดีกุล (Ph.D.) นาฏสุดา ภูมิจำนงค์ (Ph.D.) ชนินทร์ นันทเสนามาตร์(Ph.D.)

บทคัดย่อ

การศึกษาครั้งนี้มีวัตถุประสงค์เพื่อคาดการณ์การเปลี่ยนแปลงของค่าศักย์การคายระเหยของพืชอ้างอิง (ET_o) หรือการใช้น้ำของพืชอ้างอิง ภายใต้สภาพภูมิอากาศในอนาคต โดยนำรูปแบบที่ได้จากการทำเหมืองข้อมูล (Data Mining) ของสภาพภูมิอากาศที่ผ่านมาของประเทศไทย มาคาดการณ์ภายใต้เงื่อนไขการเปลี่ยนแปลงของปริมาณความเข้มข้นของก๊าซคาร์บอนไดออกไซด์ (CO_2) ในบรรยากาศ 3 ระดับคือที่ 360 ppm 540 ppm และ 720 ppm ของศูนย์เครือข่ายงานวิเคราะห์วิจัยและฝึกอบรมการเปลี่ยนแปลงของโลก แห่งภูมิภาคเอเชียตะวันออกเฉียงใต้ (SEA START RC)

การสร้างแบบจำลองระบบโครงข่ายใยประสาทเทียม (Artificial Neural Network Model) ได้ใช้นำเข้าข้อมูลภูมิอากาศย้อนหลังของประเทศไทยตั้งแต่ปี ค.ศ. 1980 – ค.ศ. 1989 ของกรมอุตุนิยมวิทยา 7 ตัวแปรได้แก่ เดือน อุณหภูมิสูงสุด อุณหภูมิต่ำสุด ค่าเปอร์เซ็นต์ความชื้น ความเร็วลมสูงสุด ความเข้มของแสงอาทิตย์ ค่าการระเหยจากถาดวัดการระเหย ใช้ข้อมูลของทั้งประเทศจำนวน 118,742 ชุดข้อมูล พบว่าแบบจำลองที่ให้ค่าความแม่นยำมากที่สุดคือ แบบจำลองที่ 6-34-1 จำนวนรอบที่ 2000 รอบ ค่าการเรียนรู้ เท่ากับ 0.1 และค่าการกระตุ้นการเรียนรู้ เท่ากับ 0.1 และนำรูปแบบของแบบจำลองมาทำการคาดการณ์การใช้น้ำของพืชในระดับความเข้มข้นของ CO_2 ทั้ง 3 ระดับให้อยู่ในรูปแบบของแผนที่แสดงค่าศักย์การคายระเหย

ผลการศึกษาพบว่าการเพิ่มระดับความเข้มข้นของปริมาณคาร์บอนไดออกไซด์ (CO_2) จะส่งผลต่อความต้องการน้ำของพืช เมื่อ CO_2 เพิ่มจาก 360 เป็น 540 ppm จะส่งผลให้มีการลดลงของการใช้น้ำของพืช 26 % ในเดือนมกราคม 5 % ในเดือนกุมพาพันธ์ 2 % ในเดือนมีนาคม 12 % ในเดือนเมษายน 18 % ในเดือนพฤษภาคม 7 % ในเดือนมิถุนายน 12 % ในเดือนกรกฎาคม 9 % ในเดือนสิงหาคม 17 % ในเดือนกันยายน 9 % ในเดือนตุลาคม 8 % ในเดือนพฤศจิกายน และ 13 % ในเดือนธันวาคม เมื่อคาร์บอนไดออกไซด์ (CO_2) เพิ่มจาก 360 เป็น 720 ppm จะส่งผลให้มีการเพิ่มของการใช้น้ำของพืชเพิ่มขึ้น 14 % ในเดือนมกราคม 2 % ในเดือนกุมพาพันธ์ 8 % ในเดือนมีนาคม 5 % ในเดือนพฤษภาคม 15 % ในเดือนมิถุนายนในขณะที่การค่าการคายระเหยของพืชลดลง 2 % ในเดือนเมษายน 3 % ในเดือนกรกฎาคม 5 % ในเดือนสิงหาคม 8 % ในเดือนกันยายน 5 % ในเดือนตุลาคม และ 8 % ในเดือน

จากนั้นได้ทำการเปรียบเทียบการใช้น้ำของข้าว พบว่าเมื่อระดับของคาร์บอนไดออกไซด์ (CO_2) เพิ่มจาก 360 เป็น 540 ppm การใช้น้ำของข้าวลดลง 18 % ในเดือนพฤษภาคม 7 % ในเดือนมิถุนายน 12 % ในเดือนกรกฎาคม 9 % ในเดือนสิงหาคม 17 % ในเดือนกันยายน และเมื่อ CO_2 เพิ่มเป็น 720 ppm จะส่งผลให้การใช้น้ำของข้าวเพิ่มเป็น 6 % และ 14 % ในหนึ่งถึงสองเดือนแรกของช่วงเวลาเพาะปลูก แต่จะมีการลดลง 3 %, 5 %, และ8 % ของการใช้น้ำของข้าวในสามถึงห้าเดือนของช่วงเวลาเพาะปลูก

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CHAPTER I
INTRODUCTION

1.1 Introduction and Background of the Study

The industrial revolution era has brought about a rise in the level of carbon dioxides (CO_2) to cause a phenomenon known as the green house effect and consequently an increase in the global temperature. Such changes are often implicated affecting the ecology and living condition. Climate change is expected to spread throughout the world and become an enduring phenomenon. (Suppakorn Chinvanno, 2004) Even Thailand cannot avoid this inevitable situation, therefore people should learn to prepare and adapt themselves for such occurrences.

Thailand is an agricultural country. After, the climate is changing that has effect to agriculture because it cannot distribute enough water for the farmer. The violent effects are losing economy and damage the earning for farmer. (Jariya Bunwat, 2004) Therefore, the way to finding method about the changing of ET_o is useful for disturbed enough water for the plant. That is difficult to do in present because of the changing of temperature.

There are many methods to discover ET_o. The popular method is Penman Monteith (Viboon Bunyatarokun, 1983). This method is calculating ET_o from data of atmosphere. This time, the atmosphere are very changing, therefore, technology are more useful to solve problem about changing of atmosphere.

From this study using Data Mining technique that are useful for manage the climate change of Thailand. During the last decade, the atmosphere is always changing. This study aim to predict the changing of ET_o under future climate pattern in the future. Data Mining is perform to predict the atmosphere in Thailand in the past. Moreover, it uses to predict ET_o in the future under climate condition of CO_2 in three levels concentration. According, those are concentration in 360 ppm 540 ppm and 720 ppm. Because of the changing of temperature in future, the result will be useful for planning using the water for the plants in many areas. This model can adapt and develop for accuracy data in the future.

1.2 Conceptual framework

The increasing of CO_2 in the atmosphere will result in changing of climate that induces in global warming. From this study, the result from climate change on evapotranspiration will effect to agriculture sector in water use which is very in water resource management in the future.

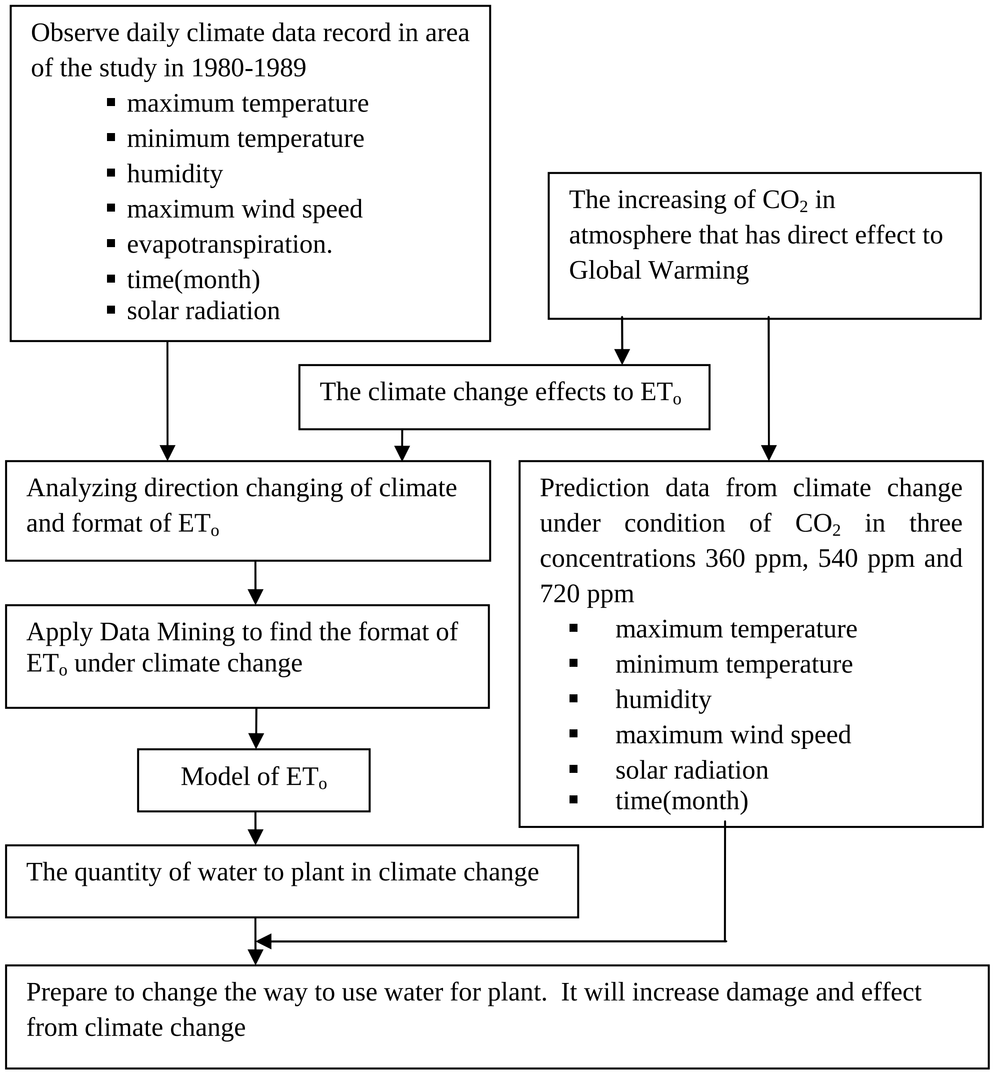


Figure 1-1 Conceptual Framework

1.3 Objective

1. To prediction ET_o using Data Mining.
2. To prediction ET_o from changing of climate pattern under different condition of atmospheric CO_2. Three conditions is the atmospheric CO_2 concentration of 360 ppm, 540 ppm and 720 ppm
3. To provide guideline how to use water in agricultural areas under effect of climate change in the future. This model can adapt and develop data to increase accuracy in the future.
4. To create the method that useful for data analysis. After study the climate change, it gets the model of diverse climate that have other Scenario.

1.4 Scope of the Study

1. Data for produce prediction model from observe daily climate information from the stations of The Thai Meteorological Department of Thailand from 1980 - 1989 and the daily solar radiation data is taken from the information stations of Department of Physic, Faculty of Science, Silpakorn University from 1980 – 1989 in the 5 regions of Thailand: Northern, Central, Eastern, Northeastern, and Western

2. The predicted daily climate data under the condition of changing atmospheric concentration of CO_2 was used for this study. The three atmospheric CO_2 concentrations are comprised of 360 ppm, 540 ppm and 720 ppm. The climate pattern under CO_2 concentrate represent of 360 ppm current conditions, while climate pattern when CO_2 concentrate of 540 ppm and 720 ppm represent climate change while could be in the middle and toward the end of the century. The information was provided by the Southeast Asia START Regional Center (SEA START RC). Includes maximum temperature, minimum temperature, precipitation, maximum wind speed, solar radiation, humidity and evapotranspiration.

3. In this study using paddy factor (Kc) in the present carbon dioxide concentration, so is a limit of study.

1.5 Expect Outcome and Benefits

1. To know the ETo in the future under changing of CO_2 from the concentration 360 ppm to 540 ppm and 720 ppm
2. To predict changes in ETo as a result of climate change under CO_2 difference condition of increased CO_2.
3. The model will be useful for predicting climate changes in various scenarios.

CHAPTER II
LITERATURES REVIEW

2.1 Definitions of climate change

Climate change in IPCC usage refers to a change in the state of the climate that can be identified (e.g. using statistical tests) by changes in the mean and/or the variability of its properties, and that persists for an extended period, typically decades or longer (IPCC, 2007). It may be caused by human activity or natural variability. On the other hand, the United Nations Framework Convention on Climate Change (UNFCCC) refers to climate change as a change of climate that is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and that is in addition to natural climate variability observed over comparable time periods (IPCC, 2007).

Increases in temperature have effects on the following managed and human systems (IPCC, 2007):

- Forestry and agricultural and management in temperate zone of Northern Hemisphere, such as changes in disturbances of forests due to fires and pests and earlier spring planting of crops (IPCC, 2007).
- Some aspects of human health, such as increases in seasonal production of allergenic pollen in Northern Hemisphere high and mid-latitudes, excess heat-related mortality in Europe, and changes in infectious diseases in parts of Europe (IPCC, 2007).
- Some human activities in the Arctic such as hunting and shorter travel seasons over snow and ice, and in lower-elevation alpine areas such as limitations in mountain sports (IPCC, 2007).

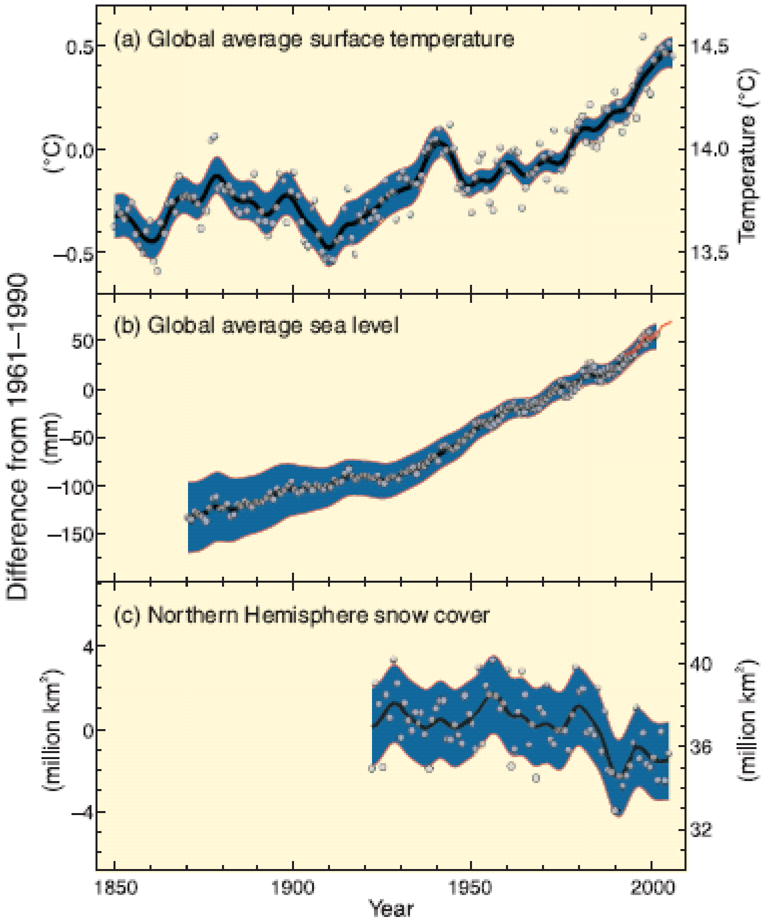


Figure 2-1 Observed changes in (a) global average surface temperature; (b) global average sea level from tide gauge (blue) and satellite (red) data; and (c) Northern Hemisphere snow cover for March-April. All differences are relative to corresponding averages for the period 1961-1990. Smoothed curves represent decadal averaged values while circles show yearly values. The shaded areas are the uncertainty intervals estimated from a comprehensive analysis of known uncertainties (a and b) and from the time series (c) (IPCC, 2007).

Losses of coastal wetlands and mangroves and increasing damage from coastal flooding in many areas are contributed sea level rise and human development. However, based on the published literature, the impacts have not yet become established trends.

2.1.1 Impacts on systems and sectors

Ecosystems

- The resilience of many ecosystems is likely to be exceeded by unprecedented combination of climate change, associated disturbances (e.g. flooding, drought, wildfire, insects, ocean acidification) and other global change drivers (e.g. landuse change, pollution, fragmentation of natural systems, overexploitation of resources).
- Over the course of this century, net carbon uptake by terrestrial ecosystems. Before mid-century is weakened or even reverse16, thus amplifying climate change.
- Approximately 20 to 30% of plant and animal species assessed are *likely* to increased risk of extinction. Increasing global average temperature exceed 1.5 to 2.5°C.
- To increases global average temperature exceeding 1.5 to 2.5°C concomitant atmospheric CO_2 concentrations. The major projected changes in ecosystem structure and function, species' ecological interactions and species' geographical ranges with predominantly negative consequences for biodiversity and ecosystem goods and services, e.g. water and food supply.

Food

- Crop productivity is projected to increase slightly at mid to high latitudes for local mean temperature increases up to 1 to 3°C, and decrease beyond in some regions.
- At lower latitudes, especially in seasonally dry and tropical regions, crop productivity to decrease for even small local temperature increases (1 to 2°C), which increase the risk of hunger.
- Globally, the potential for food production is projected to increase in local average temperature over a range of 1 to 3°C, but above this to decrease.

Coasts

- Coasts are projected to be exposed to increasing risks and coastal erosion, due to climate change and sea level rise. The effect will be exacerbated by human-induced pressures on coastal areas.

- By the 2080s, every year many millions people are projected to experience floods due to sea level rise. The numbers affected will be largest in the densely populated and low-lying megadeltas of Asia and Africa while small islands are vulnerable.

Industry, settlements and society

- The most vulnerable industries, settlements and societies are generally in coastal and river flood plains, economies are closely linked with climate-sensitive resources and prone to extreme weather events, especially rapid urbanisation will occurring.
- Poor communities concentrated in high-risk areas.

Health

- The health status millions of people is projected to be affected through, for example, increases in malnutrition, deaths, burden of diarrhoeal diseases , frequency of cardio-respiratory diseases due to higher concentrations of ground-level ozone in urban areas related to climate change , diseases and injury due to extreme weather events, and the altered spatial distribution of some infectious diseases.
- Climate change is projected to bring some benefits in temperate areas, such as, fewer deaths from cold exposure and mixed-effects (changes in range and transmission potential of malaria in Africa). Overall it is expected benefits will be outweighed the negative health effects of rising temperatures, especially in developing countries.
- Important critical, factors will be directly shape the health of populations such as education, health care, public health initiatives, and infrastructure and economic development.

Water

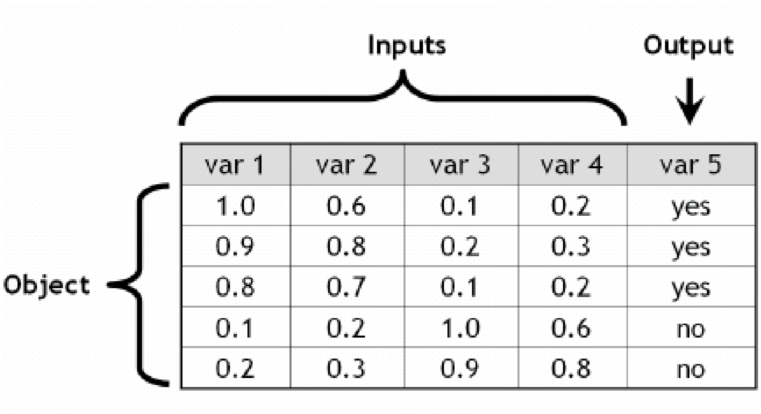
- Water impacts are keys for all sectors and regions. These are discussed below in the Box 'Climate change and water'.

2.2 DATA MINING

Data mining refers to technology that utilizes mathematical algorithms to discover new knowledge on existing datasets in the form of prediction, classification, association, clustering, etc (Han and Kamber, 2001). When the valuable information of interest has to be extracted, it is like finding a needle in haystacks. Many algorithms and applications are use for data mining. An example of data mining can be found at supermarkets in which accumulated data regarding customer's shopping behavior are used to mine useful information. Customers who buy toothbrushes are likely to buy toothpaste; therefore, supermarkets could offer discounts for customers who purchase toothbrush together with toothpaste as a potential means to increase revenues (Chanin Nantasenamat, 2006).

2.2.1 Data

Data are the essential information is used for the construction of a predictive model. The quality of prediction depends on the quality of data. Each row represents an object of the dataset; column refers to the variables of the dataset. Variables 1 to 4 are input data mining system, variable 5 is the output. The output data is usually referred to as the class or class label. In this particular, example, the values of the output (class) are nominal or discrete values denoted as either yes or no. In this example, it can be seen variables 1 and 2 have low values, while variables 3 and 4 have high values; variable 5 has the class label of no. Thus, new data object has same trend, it would be predicted to have a class label of no.



var 1	var 2	var 3	var 4	var 5
1.0	0.6	0.1	0.2	yes
0.9	0.8	0.2	0.3	yes
0.8	0.7	0.1	0.2	yes
0.1	0.2	1.0	0.6	no
0.2	0.3	0.9	0.8	no

Figure 2-2 A typical dataset (Chanin Nantasenamat, 2006).

2.2.2 Cross-validation

Cross-validation is the practice of dividing the dataset into *n* equal parts and using one part as the test set while the remaining parts as the training set. Practice allows all objects of the dataset to be sampled and prediction, which provides an unbiased way to sample the dataset. For example, a dataset with 1,000 objects can be divided into 10 equal parts of 100 objects where one part containing 100 objects are used as the test set while the remaining 900 objects are used as the training set. The previous example is called 10-fold cross-validation. The number of folds may range up to the number of objects, which in this case is called the leave-one-out cross-validation that used for datasets to contain few numbers of objects.

2.2.3 Methodology of Data Mining

The protocol for performing data mining is rather subjective which it is prone to bias by the individual or organization that carries out the task. An initiative called "Cross Industry Standard Process for Data Mining" (CRISP-DM) was established by Daimler Chrysler, SPSS, and NCR in 1996. The aim is to develop a universal protocol on the processes of data mining that is not specific to a given industry but applicable to all (SPSS, 2005). The benefit is all industries could reap data mining regardless of discipline and financial budget in acquiring the "know-how". The methodology drafted by CRISP-DM is claimed to make data mining projects "faster, cheaper, more reliable and more manageable." The methodology of performing data mining as set out by CRISP-DM consists of the following six phases:

1) Business/ Research Understanding
- Understand Project Objectives and Requirements
- Design a data mining plan that fulfill with the Project Objectives and Requirements

2) Data Understanding
- Data collection
- Observe general descriptions and summarization data
- Identify data quality problems

- Discover and detect "interesting subsets to form hypotheses for hidden information"

3) Data Preparation

- Clean and Transform raw data into a final dataset that serve as input for modeling tools

4) Modeling

- To select appropriate modeling technique
- Optimize parameters for the modeling tool

5) Evaluation

- To evaluate the exhaustively model
- Assess steps taken to construct the model that it assure the project objectives
- Decision use or reject the model

6) Deployment

- To organize and present data
- To critique the project (right or wrong)
- To summarize the decision during the project as to facilitate future implementation of the similar project.

2.2.4 Model Construction

The essential data mining lies in the creation of the predictive model that is responsible for generating “knowledge,” which may be in the form of prediction, classification, clustering, etc. The dataset is divided into two components: 1) training set and 2) test set. The construction of the model requires the machine learning algorithm by examples from the training set. The combined knowledge is employed to make predictions on the test set.

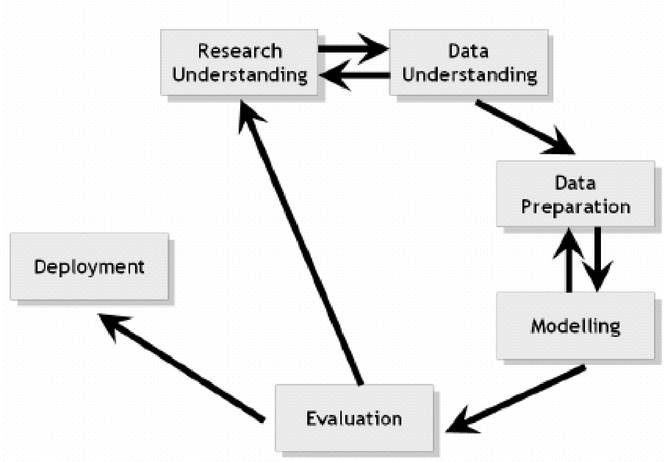


Figure 2-3 Methodology of the Data Mining process as outlined by CRISPDM (Adapted from SPSS, 2005).

Backpropagation neural network is prediction model contains information to the importance of the connection weights existing among the neural network. It should be noted the values of weights are optimized by the errors backpropagation.

2.2.5 Knowledge Representation

Machine learning algorithms are applied to extract patterns. The types of patterns can be discovered from the data classification, prediction, clustering, association, and regression (Han and Kamber, 2001).

Classification involves with the construction of a model by utilizing a set of training data with known class labels. It can be used to predict nominal classes, which refers to discrete values.

The model is used to predict the class label for a set of test data with unknown class labels (Han and Kamber, 2001; SPSS, 2005).

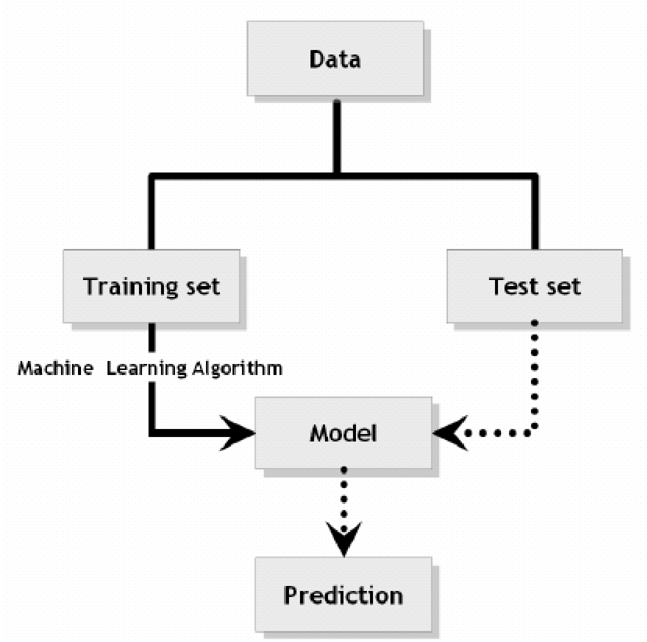


Figure 2-4 Flow chart of model construction and data prediction.

Prediction is similar to classification with the difference being that the class is a continuous numerical value instead of a nominal one. For example, numerical values with decimals are considered to be continuous (Han and Kamber, 2001).

Clustering is similar to classification which the data are assigned class labels, however, the class label is unknown and need to be derived and generated from the input variables (Han and Kamber, 2001).

Association describes connection between two data objects. It is extensively used for market basket or transaction data analysis, for instance, customers purchasing potato chips are likely to buy a six pack of cola (Han and Kamber, 2001).

Regression is statistic analysis that used to “extrapolate trends from a few samples of data.” The formula used for extrapolation is a linear equation in the form of $y = mx + b$; m is the slope of the line, b is the y-intercept, and x and y are the coordinates on the plot (Bergeron, 2003).

2.2.6 Supervised versus Unsupervised Learning

Learning is defined by Merriam-Webster as “to gain knowledge or understand of skill by study, instruction, or experience” (Merriam-Webster, 2005). Types of learning are supervised and unsupervised learning. Supervised learning is performed on datasets with known outputs (the variable of interest that is to be predicted). The dataset contain of output values that is possible for the algorithm to adapt its performance in accordance with the error, which is common in the backpropagation neural network (Zupan and Gasteiger, 1999). Unsupervised learning refers to the classification or prediction of the class it belongs to with no prior knowledge of its output value. On the other hand, there is the presence of output values for the supervised learning datasets, training and test set are required for the evaluation of the prediction performance. Therefore in unsupervised learning, all objects of the dataset are used to produce a map that displays the clustering of relevant objects of the dataset closer to another while objects that are irrelevant. In this thesis, the supervised learning method is used to predict the parameter of interest, which will be discussed later.

2.2.7 Machine Learning Algorithms

The algorithms of Data Mining can be called Machine Learning algorithms or simply learning algorithms. Many types of learning algorithms are available for implementing data mining and depend on the nature of the dataset. Some learning algorithm well works for certain dataset while worse on others. Some of the most popular learning algorithms include Apriori Algorithm, Decision Tree Induction, Bayesian Classification, Neural Network, Genetic Algorithm, k-Nearest Neighbor Classifiers, Rough Set Approach, Fuzzy Set Approach, etc (Witten and Frank, 2000).These learning algorithms are focus on this thesis and the Backpropagation Neural Network will be discussed. For more information, please see (Han and Kamber, 2001; Witten and Frank, 2000; Hand et al., 2001).

2.2.8 Artificial Neural Network

The brain is “a huge network of nerve cells or neurons that are specialized to carry messages in the form of electrochemical signals.

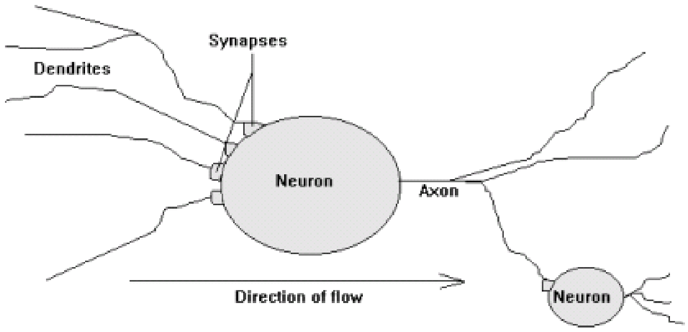


Figure 2-5 Sketch of a typical neuron (Hand et al., 2001).

As can be seen from the Figure above, the nerve cell is composed of the dendrites, cell body (neuron), and axons. The connection between the axons of one nerve cell with the dendrites is referred to as a synapse which is signals transmitted from one cell to the next in form of neurotransmitters.

The artificial neuron is illustrated in Figure 2.6 where variables w_1, w_2, and w_n refer to weights of the connections between nodes of one layer to the next. The various layers are assigned numerical values known as weights, which express the relative strength of the input data (Zupan and Gasteiger, 1999). The connection of weights from neurons of preceding layers to a neuron of the next layer is called the synapse. Each node contains two components, namely the summation function and the transfer function. The summation function is computed from the weighted sum of all input node entering each hidden node. It consolidates the weights of the neuron into a single value that can be passed to the transfer function for processing.

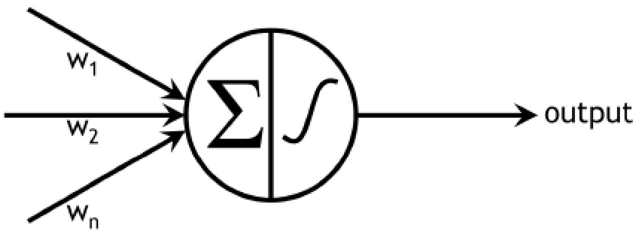


Figure 2-6 Sketch of an artificial neuron.

The summed weight is passed onto the second part of the neuron, known as the transfer function so the value could be converted into a scaled value depending on the type of transfer function used (Zupan and Gasteiger, 1999). The role of the transfer function is translating the summed information into outputs. For example, the hard-limiter transfer function has two values, either zero or one. Once a threshold is reached the value is rounded off to the nearest number. The values are below 0.5 could be rounded off to 0 while values greater than 0.5 could be rounded off to 1. The most popular transfer function and another one used in this work is the sigmoid transfer function, which is characterized by a transfer function with a sigmoid curve.

2.2.9 Overview of Artificial Neural Network Architecture

A majority of neural networks comprises of three layers; the input, hidden, and output layer. The input layer receives input data, the hidden layer is the transfer function (B), Threshold transfer function (C), and Sigmoid transfer function (D). Adapted from (Zupan and Gasteiger, 1999).internal layer that performs processing and transformation of the input data, and the output layer relay the final results that each layer contains neurons (nodes). The numbers of nodes present input and output layer depends on the number of variables in the dataset. On the other hand, the numbers of nodes used for the hidden layer are obtained through trial-and-error.

The learning process starts with random seeding of the connection weights (Agatonovic-Kustrin and Beresford, 2000; Niculescu, 2003) and signals are propagated from the input layer through the hidden layer to the output layer. A neural network is trained by adjusting the weights until they reach an optimal set. The predicted output is as close as to the actual output for many input objects present in the dataset (Zupan and Gasteiger, 1999). There are many learning algorithms in neural network and each method in different way weights are adjusted. One of the supervised learning methods used in this thesis is neural network implementing the back-propagation algorithm. Briefly, it involves the correction of weights starting from the output layer and working its way backwards towards the input layer. Afterwards the weights are adjusted accordingly with respect to the error, which are calculated from the difference between the actual and predicted value (Zupan and Gasteiger, 1999).

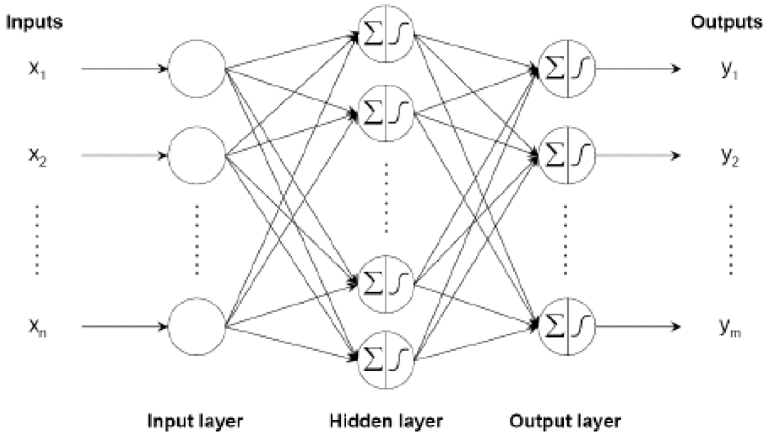


Figure 2.7 Schematic representation of a three-layer feed-forward backpropagation neural network. Circles represent nodes (neurons), while the connection between nodes represents weights. The summation and sigmoidal symbol found inside hiddle nodes and output layer transfer function, respectively**.**

The learning rate (η) constant determines the speed at which the weights change, while the momentum (μ) constant prevent sudden changes in attaining the solution (Zupan and Gasteiger, 1999). One complete cycle of data propagated in a feed forward manner through the layers of the neural network is referred to as an epoch.

The root mean square error (RMS) is a measure of the prediction error exhibited by the trained model and is calculated with the following equation:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(p_i - a_i)^2}{n}}$$

Where *i p* is the predicted output, *i a* is the actual output, and *n* is the number of compounds in the testing set.

2.3 Reference crop evapotranspiration (ET_o)

The evapotranspiration rate from a reference surface, not short of water, is called the reference crop evapotranspiration or reference evapotranspiration. It is denoted as ET_o. The reference surface is a hypothetical grass reference crop with specific characteristics. The use of other denominations such as potential ET is strongly discouraged due to ambiguities in their definitions.

The concept of the reference evapotranspiration was introduced to study the evaporative demand of the atmosphere independently of crop type, crop development and management practices. As abundantly water is available at the reference evapotranspiring surface, soil factors do not affect to ET. Relating ET a specific surface provides a reference to ET from other surfaces can be related. It obviates the need to define a separate ET level for each crop and stage of growth. ET_o values measured or calculated at different locations or different seasons are comparable as they refer to the ET from the same reference surface.

The only factors affecting ET_o are climatic parameters. Consequently, ET_o is a climatic parameter and can be computed from weather data. It expresses the evaporating power of the atmosphere at a specific location and time of the year does not consider the crop characteristics and soil factors. The FAO Penman-Monteith method is recommended as the sole method for determining ET_o. This method has been selected because it closely approximates grass ET_o at the location evaluated, is physically based, and explicitly incorporates both physiological and aerodynamic parameters. Furthermore, procedures have been developed for estimating missing climatic parameters.

2.3.1 Equation

A consultation of experts and researchers was organized by FAO in May 1990, in collaboration with the International Commission for Irrigation and Drainage and the World Meteorological Organization, to review the FAO methodologies on crop water requirements and advice on the revision and update of procedures.

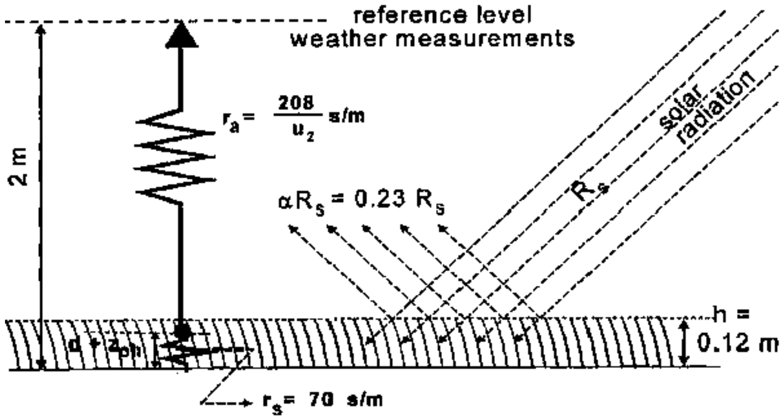


Figure 2-8 Characteristics of the hypothetical reference crop.

The panel of experts recommended the adoption of the Penman-Monteith combination method as a new standard for reference evapotranspiration and advised on procedures for calculation of the various parameters. By defining the reference crop as a hypothetical crop with an assumed height of 0.12 m having a surface resistance of 70 s m^{-1} and an albedo of 0.23, closely resembling the evaporation of an extension surface of green grass of uniform height, actively growing and adequately watered, the FAO Penman-Monteith method was developed.

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}$$

where, ET_o reference evapotranspiration [mm day^{-1}],

R_n net radiation at the crop surface [MJ m^{-2} day^{-1}],

G soil heat flux density [MJ m^{-2} day^{-1}],

T mean daily air temperature at 2 m height [°C],

u_2 wind speed at 2 m height [m s^{-1}],

e_s saturation vapour pressure [kPa],

e_a actual vapour pressure [kPa],

e_s - e_a saturation vapour pressure deficit [kPa],

D slope vapour pressure curve [kPa $°C^{-1}$],

g psychrometric constant [kPa $°C^{-1}$].

The FAO Penman-Monteith equation is simple representation of the physical and physiological factors governing the evapotranspiration process. By using the FAO Penman-Monteith definition for ET_o, one may calculate crop coefficients at research sites by relating the measured crop evapotranspiration (ET_c) with the calculated ET_o, i.e., $K_c = ET_c/ET_o$. In the crop coefficient approach, differences in the crop canopy and aerodynamic resistance relative to the hypothetical reference crop are accounted for within the crop coefficient. The K_c factor serves as an aggregation of the physical and physiological differences between crops and the reference definition.

2.4 Research in climate change, ANNs and evpotranspiration

Goyal, R.K. (2004) identified the major factors to be used in Penman's-Monteith equation. The study showed that when evapotranspiration (ET) increased by 14.8%, temperature increased by 20%, net solar radiation increased by 11%, and wind speed increased by 7%.

Fulu Tao, et.al. (2002) simulated the future climate condition using HADCM2 model and used the result from the model together with FAO Penman's equation and found that ETa^c increase 20 mm/day and ETo^c increase 10 mm/day.

Eduardo J.de Brito Bastos, et.al. (2000) concluded that Penman's-Monteith equation was more reliable when compared to Caselles et al.'s (1992b) and Jensen & Haise's (1963) equations. The study used GOES-8 data to estimate potential evapotranspiration (ETo) and found that Caselles et al.'s (1992b) and Jensen & Haise's (1963) equations had 20% error.

S. chakraborty, et.al. (1999) studied potential climate change effect on plant diseases and found both negative and positive impacts. The result showed that plant diseases and pest outbreak increased when temperature increased 2ºC and 4ºC.

Somvang Bouttavong, et.al.: (2006) studied An application of climate change scenarios in studying the effect of climate change on crop water requirement and water balance in a reservoirn : a case study of the planned Nam Nga Gnai reservoir project, Sanakham district, Vientiane province, Lao PDS. This research calculated ETc used climate data on CO_2 360 ppm, 540 ppm, and 720 ppm. The result is CO_2 concentration in atmosphere was increased effect to ETc.

Aukit Putchim, (2001) studied Application of Data Mining Technique for Maximum Water Level Prediction. This research used 5 stations data in Chaopaya river transforms Data Mining was used k-mean. Clustering application and ANNs application, the result model had R-square 0.8

Marutt Kawemanee (2007) studied Estimation of Dynamic Suspended Sediment in The River Basin using Artificial Neural Networks,: A case study of upper Lum Ta Kong basin. This research used ANNs model for predicted sediment in river. Comparison between ANNs model and actual sediment, the result was nearly.

M. Kumar, et.al.: (2002) Estimating Evapotranspiration using Artificial Neural Network. This research used ANNs model compared Penman's-Monteith equation and used data from Davis California Irrigation in 6 variable; solar radiation, maximum temperature, minimum temperature, maximum humidity, minimum humidity and wind speed for bullied architecture for ANNs model. The result is ETo from ANNs model better than Penman's-Monteith equation.

S.S. Zanetti, et.al.: (2007) Estimating Evapotranspiration Using Artificial Neural Network And Minimum Climatological Data. This research was studied ETo used ANNs model from minimum climate data. The climates data were solar radiation, maximum temperature, minimum temperature, and sunshine hour from stations Campos dos Goytacazes in Rio de Janeiro and Vicosa in Minas Gerais. The result is ETo from ANNs model better than Penman's-Monteith equation.

Supparkorn Chinvanno (2004) Climate change in Thailand, the summary of the prediction climate from Conformal Cubic Atmospheric Model (CCAM). The result is CO_2 concentration in atmosphere increased from 360 ppm to 540 ppm and 720 ppm. The effect of Climate had rainfall would increased but temperature was not increased once other hand hot day and cold day were increased.

Sahaschai Kongton et.al.(2002) Impact of Climate Change on Maize Sugarcane and Cassava Production in N.E. Thailand : Study area at Khon Kaen province. This research used climate data from CCAM to predict product of Maize, Sugarcane and Cassava used CERES Maize model, GUMCAS model and CANEGRO. The result show the Maize and Sugarcane had high growth rate and yield will increased but Cassava had low growth rate and yield will decreased.

Nattapong Supmaneenan (2003) A Study on The Consumptive use of Water Hyacinth, Water Lettuce and Duckweed. This research compared ET Water Hyacinth, Water Lettuce and Duckweed from lysimeter, Thornthwaite equation, Blaney-Criddle equation, Makkink equation, Jensen-Haise equation and Penman's-Monteith equation. The result is ET Water Hyacinth, Water Lettuce and Duckweed was 6.01, 4.86 and 4.33 mm/day. The comparison had shown Penman's-Monteith equation better.

CHAPTER III
METHODOLOGY

This chapter describes the procedure of potential evapotranspiration (ET_o) prediction due to climate change in Thailand. The study focuses only on the changing condition of CO_2 quantity in the atmosphere. Data Mining technique was used as a main method to estimate the change in ETo.

3.1 Equipment and material

1) Hardware
- Processor: Intel® Core™ 2 Quad processor Q6600
- (2.40 GHz, 1066 MHz FSB, 8 MB L2 cache)
- VGA ASUS EN8500GT PCI 512 MB DDR2
- Memory 4 GB of RAM

2) Software
- Operation system: Microsoft Window XP
- (Professional Version 2002 Service Pack 2)
- DirectX version: DirectX 9.0c
- Weka 3.5.7
- Microsoft Office
- ARCGIS
- UltraEdit-32 Text Editor

3.2 Data

1. Observed daily climate data from the Thai Meteorological Department of Thailand in 1980-1989. The variables includes:
   - maximum temperature
   - minimum temperature
   - humidity

- maximum wind speed
- evapotranspiration.
- time(month)
- solar radiation

2. Observed daily solar radiation data from the Department of Physic, Faculty of Science, Silpakorn University 1980 – 1989.

3. Projected daily climate data under three different CO_2 conditions atmospheres concentrates of 360 ppm, 540 ppm and 720 ppm, hereinafter, will be referred as climate scenario 1, scenario 2 and scenario 3. The climate scenario 1 represents the present time, the climate scenario 2 represents the middle of the century, and the climate scenario 3 represents the end of the century (the data provide by SEA START RC). The data, which is daily data, will be grouped together into monthly step for further analysis. The variables includes:

    - maximum temperature
    - minimum temperature
    - humidity
    - maximum wind speed
    - solar radiation

3.3 Methodological Framework

After climate change phenomenon was realized, the Thai Meteorological Department had collected the data since 1980 to 1989. This data is used in Data Mining process. The data was searched for the relationship among variables before inputting into the Artificial Neural Networks (ANNs). The developed ANNs were then used to predict the ET_o under three CO_2 concentrations 360 ppm, 540 ppm, and 720 ppm.

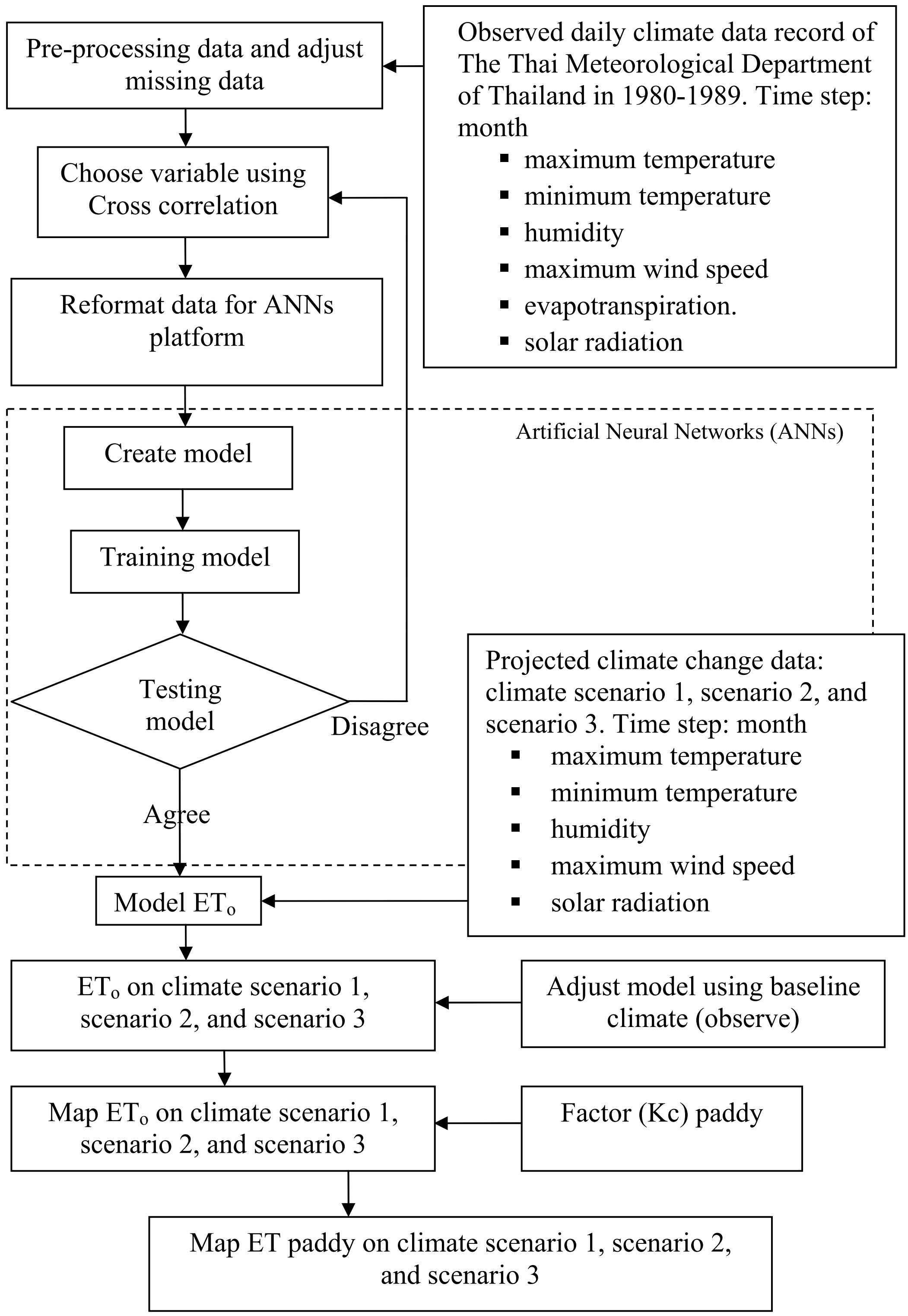


Figure 3-1: Methodological Framework

3.4 Method

3.4.1 Collection and Analysis of Data

Observed daily climate data record of The Thai Meteorological Department of Thailand in 1980-1989. Time step: month

- maximum temperature
- minimum temperature
- humidity
- maximum wind speed
- evapotranspiration.
- solar radiation

Table 3-1 List of station in study area

STATION INFORMATION						
STATION	LATITUDE			LONGITUDE		
NORTHERN PART						
MAE HONG SON	19	18	N	97	50	E
MAE SARIANG	18	10	N	97	56	E
CHIANG RAI	19	55	N	99	50	E
PHAYAO	19	8	N	99	54	E
CHIANG MAI	18	47	N	98	59	E
LAMPANG	18	17	N	99	31	E
LAMPHUN	18	34	N	99	2	E
PHRAE	18	10	N	100	10	E
NAN	18	47	N	100	47	E
THA WANG PHA	19	7	N	100	48	E
THUNG CHANG	19	24	N	100	53	E
UTTARADIT	17	37	N	100	6	E
TAK	15	53	N	99	7	E
MAE SOT	16	40	N	98	33	E
BHUMIBOL DAM	17	14	N	99	3	E
UMPHANG	16	1	N	98	53	E
PHITSANULOK	16	47	N	100	16	E
PHETCHABUN	16	26	N	101	9	E
LOM SAK	16	46	N	101	15	E
WICHIAN BURI	15	39	N	101	7	E
KAMPHANG PHET	16	48	N	99	53	E
NORTHEASTERN PART						
NONG KHAI	17	52	N	102	44	E
LOEI	17	27	N	101	44	E
UDON THANI	17	23	N	102	48	E
SAKON NAKHON	17	9	N	104	8	E
NAKHON PHANOM	17	25	N	104	47	E
KHON KAEN	16	26	N	102	50	E
MUKDAHAN	16	32	N	104	45	E
KOSUM PHISAI	16	15	N	103	4	E
CHAIYAPHUM	15	48	N	102	2	E
ROI ET	16	3	N	103	41	E
UBON RATCHATHANI	15	15	N	104	52	E

STATION INFORMATION

STATION	LATITUDE			LONGITUDE		
NAKHON RATCHASIMA	14	58	N	102	5	E
CHOK CHAI	14	44	N	102	11	E
SURIN	14	53	N	103	30	E
THA TUM	15	19	N	103	41	E
NANG RONG	14	37	N	102	43	E
CENTRAL PART						
NAKHON SAWAN	15	48	N	100	10	E
SUPHAN BURI	14	28	N	100	8	E
LOP BURI	14	48	N	100	37	E
BUA CHUM	15	16	N	101	12	E
PILOT STATION	13	22	N	100	36	E
KANCHANABURI	14	1	N	99	32	E
THONG PHA PHUM	14	45	N	98	38	E
BANGKOK METROPOLIS	13	44	N	100	34	E
BANGKOK PROT (KLONG TOEY)	13	42	N	100	34	E
DON MUANG (AIRPORT)	13	55	N	100	36	E
EASTERN PART						
PRACHIN BURI	14	3	N	101	22	E
KABIN BURI	13	59	N	101	42	E
ARANYAPRATHET	13	42	N	102	35	E
CHON BURI	13	22	N	100	59	E
KO SICHANG	13	10	N	100	48	E
PATTAYA	12	55	N	100	52	E
SATTAHIP	12	41	N	101	1	E
LAM CHABANG	13	4	N	100	52	E
RAYONG	12	38	N	101	21	E
CHANTHABURI	12	37	N	102	7	E
KHLONG YAI	11	46	N	102	53	E
SOUTHERN PART (EAST COAST)						
PHETCHABURI	13	9	N	100	14	E
PRACHUAP KHIRI KHAN	11	50	N	99	50	E
HUA HIN	12	35	N	99	58	E

1. Observed daily solar radiation data inside study area of Department of Physic, Faculty of Science, Silpakorn University 1980 – 1989.
2. The projected climate data: climate scenario 1, climate scenario 2, and climate scenario 3. Time step: month
   - maximum temperature
   - minimum temperature
   - humidity
   - maximum wind speed
   - solar radiation

3.4.2 Data pre-processing

Trend analysis was performed on climate data variables.

1. The variables were used to perform a linear regression to derive the Correlation Coefficient (R). The correlation coefficient can be obtained from the equation below.

$$r = \frac{\sum_{i=1}^{n}\left[\left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)\right]}{\sqrt{\left[\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2 \sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2\right]}}$$

Where; *R* represents Correlation Coefficient between variables x and y

Ɛ *x* Ɛ *y* represents total measured total from x and y, respectively

Ɛ *xy* represents total multiplication between x and y

Ɛ x_2Ɛ y_2 represents power square of data from x and y, respectively

N represents sampling

After pre-processing, relationship among climate variables is understood.

3.4.3 Reformatting data for ANNs platform

1. Variables were process using normalize equation in order to get data in the format required by ANNs platform before input to training model.

$$X' = \frac{\left(X - X_{\min}\right)}{\left(X_{\max} - X_{\min}\right)}$$

Where;

X′	=	data normalized
X	=	variable data
X_{max}	=	maximum variable data
X_{min}	=	minimum variable data

2. Variables that had maximum correlation coefficients were selected to create model for Artificial Neural Networks (ANNs). Following the steps bellows.

1) random weights and bias factors
2) input (I1, I2,….In) and output (t1, t2,…tn)
3) layer m = 1, 2,…I

Calculate Nj, m of neuron j in layer m

$$N_{j,m} = \sum_{i=1}^{n_{m-1}} W_{ji,m} O_{i,m-1} + \theta_{j,m}$$

Where, Nj, m	=	activation of neuron j in layer m
Oi, o	=	Ii
tj	=	target value of neuron j in output layer
Oj,m	=	output of neuron j in layer m
θj,m	=	bias value for neuron j in layer m
Wji,m	=	synaptic weight between node j in layer m and node i in layer m-1
nm	=	number of neuron in layer m

Calculate output Oj, m of j in layer m

$$O_{j,m} = \frac{1}{1-e^{-n_{j,m}}}; j = 1,2,...nm$$

3. Transforming input from layer m-1 to output in layer m

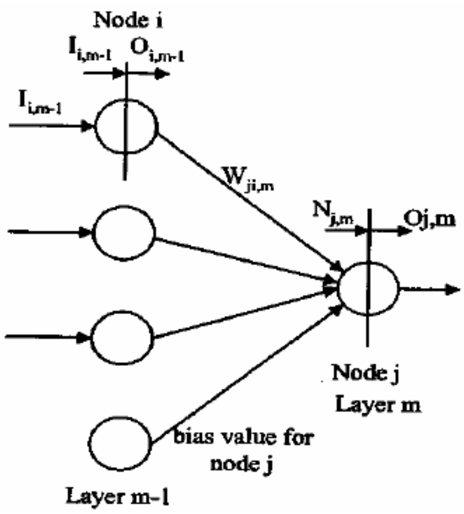


Figure 3-2 Transforming input from layer m-1 to output in layer m (varavuit, 2001).

4. revise layer m = I, I-1, I-2,….1

δj, m= value of δ for neuron j in layer m

a. calculate

output layer m

$$\delta_{j,m} = o_{j,m}\left(1 - o_{j,m}\right)\left(t_j - o_{j,m}\right);$$

hidden layer m

$$\delta_{j,m} = O_{j,m}\left(1 - O_{j,m}\right)\sum_{k=1}^{n_{m-1}} W_{kj,m+1}\delta_{k,m+1};$$

b. adjust weight

$$\Delta W_{ji,m}\left(n+1\right) = \eta \cdot \delta_{j,m} O_{i,m+1} + \alpha \cdot \Delta W_{ji,m}(n)$$

where, η = learning parameter

α = momentum parameter

$\Delta W_{ji,\,m}$ (n) = weight change between node j in layer m and node I at n iteration

$\Delta W_{ji,\,m}$ (n + 1) = weight change between node j in layer m and node I at n+1 iteration

$O_{i,m-1}$ = Ii, m

n = number of iteration (n = 1, 2, 3,…)

c. recalculate weights

$$W_{ji,m(n+1)} = W_{ji,m(n)} + \Delta W_{ji,m(n+1)}$$

where, Wji, m (n) = weight value between node j in layer m and node i at n iteration

Wji, m (n+1) = weight value between node j in layer m and node i at n+1 iteration

3.4.4 Compare result from ANNs model with annual ET_o(observer) and Modified Penman equation

Compare ET_o from ANNs with observer ETo(reserved data set) and also compare with Modified Penman.

3.4.5 Estimate the ET_o using projected climate data and adjustment data

The projected climate data: climate scenario 1, climate scenario 2 and climate scenario 3, were used as input into the ANNs model and use baseline ET_o data to adjust result from model.

3.4.6 Produce ET_o map

Produce ET_o map and ET paddy map from ANNs output using ArcGIS.

Map producing steps:

1) Input ET_o data: climate scenario 1, scenario 2 and scenario 3 to ARCGIS.
2) Classify ET_o data from climate scenarios.
3) Interpolate data from point to contour maps.
4) Clip contour maps by Thailand boundary.
5) Compare ET paddy between climate scenario 1, scenario 2 and scenario 3.
6) Produce ET paddy maps on climate scenario 1, scenario 2 and scenario 3.

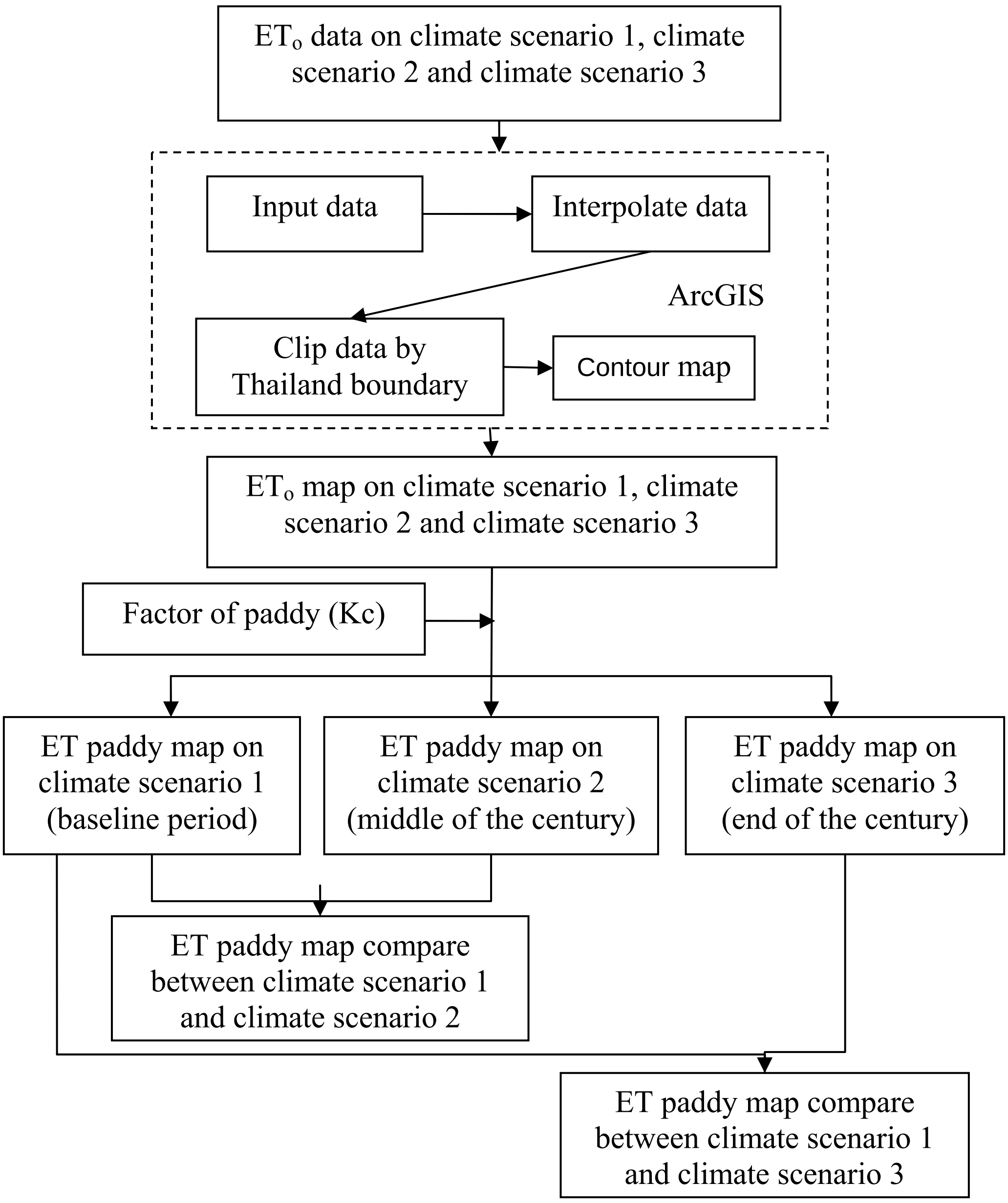


Figure 3-3 Step to produce ET paddy map**.**

CHAPTER IV
RESULTS AND DISCUSSION

4.1 Data analysis

Correlation is the association between 2 variables through the application of correlation coefficient to determine the level of association and direction. Choose data about 118,742 from The Thai Meteorological Department of Thailand in 1980-1989. Adjust missing data by cut of missing data from all observer data before find the correlation value.

Table 4-1 Correlation between variable with ET_o.

variable	R	R Square
Time(month)	-0.275	0.0753636495
Maximum temperature	0.598	0.3570732024
Minimum temperature	0.271	0.0733368357
humidity	-0.544	0.2955324787
Maximum wind speed	0.298	0.0888043496
Solar radiation	0.323	0.1041363835

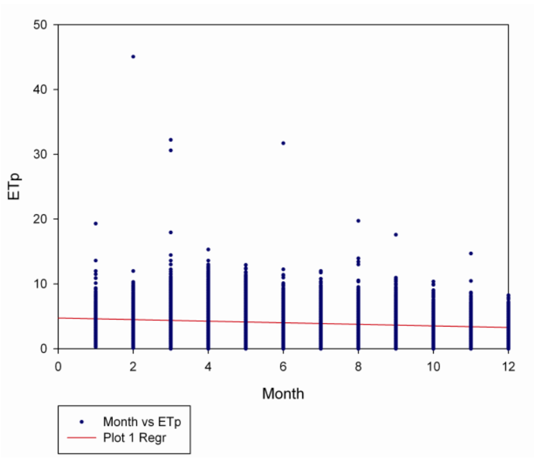


Figure 4-1 Association between Time step (month) with ET_o.

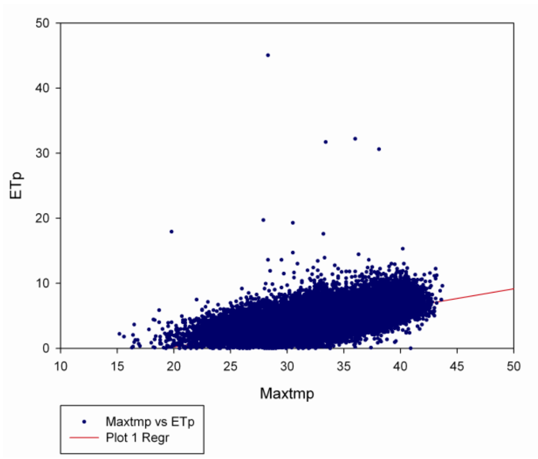


Figure 4-2 Association between Maximum temperatures with ET_o.

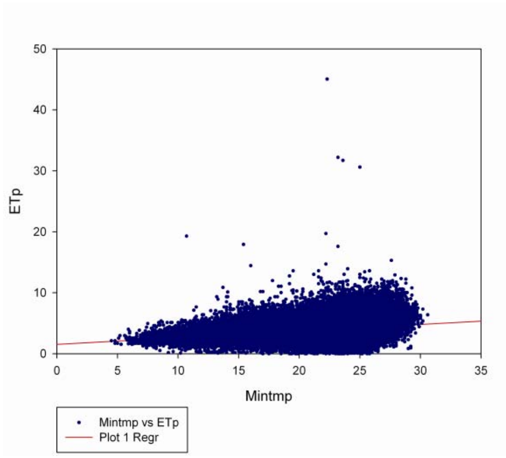


Figure 4-3 Association between Minimum temperatures with ET_o.

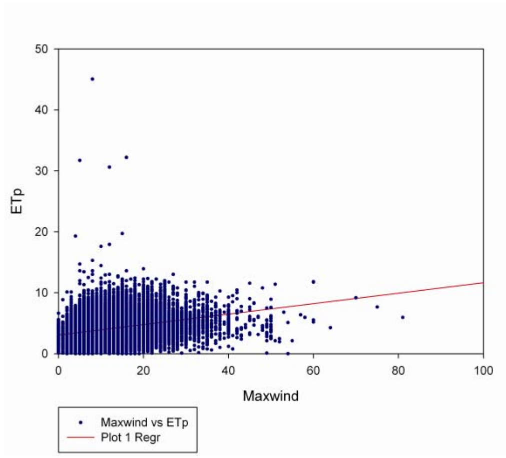


Figure 4-4 Association between Maximum wind speeds with ET_o.

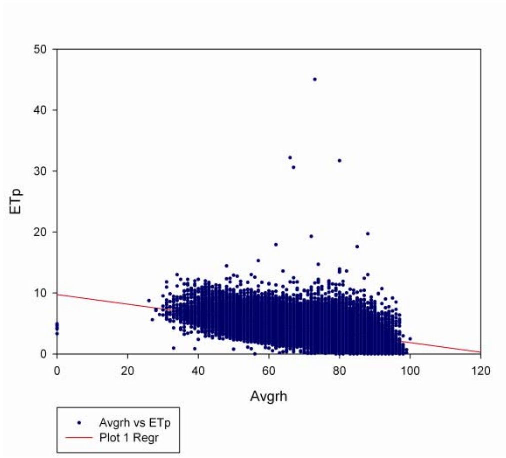


Figure 4-5 Association between Humidity with ET_o.

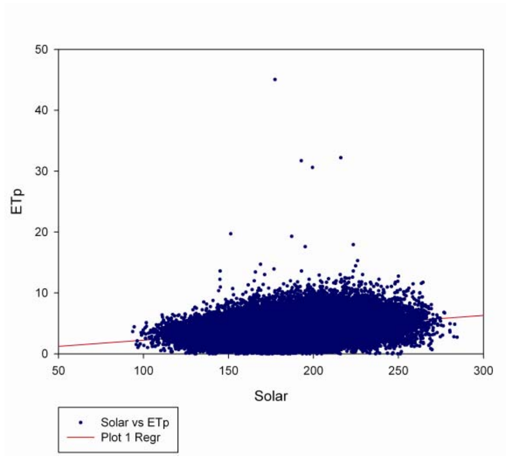


Figure 4-6 Association between Solar radiations with ET_o.

4.2 Find the architectures ANNs

Process in finding appropriate ANNs architectures, which will give minimum RMSE, is base on 10 repetitive sum of ANNs model.

4.2.1 Choose variable for the first model

The variable for the first model are maximum temperature and humidity because are maximum correlation.

4.2.2 The First model's hidden node

The first, model ANNs must searching amount of Hidden node because it has effect to RMSE by test are 1 to 50 hidden nodes.

Table 4-2 Architectures of the tested the first model's Neural Networks.

Network architecture	RMSE
2-1-1	1.248
2-2-1	1.244
2-3-1	1.242
2-4-1	1.240
2-5-1	1.236
2-6-1	1.227
2-7-1	1.226
2-8-1	1.226
2-9-1	1.225
2-10-1	***1.223***
2-11-1	1.223
2-12-1	1.223
2-13-1	1.223
2-14-1	1.223
2-15-1	1.223
2-16-1	1.223
2-17-1	1.223
2-18-1	1.222
2-19-1	1.223
2-20-1	1.223
2-21-1	1.223
2-22-1	1.223
2-23-1	1.223
2-24-1	1.223
2-25-1	1.223
2-27-1	1.223
2-28-1	1.222
2-29-1	1.223
2-30-1	1.223
2-31-1	1.223
2-32-1	1.223
2-33-1	1.223
2-34-1	1.222
2-35-1	1.223
2-36-1	1.222
2-37-1	1.223
2-38-1	1.223
2-39-1	1.223
2-40-1	1.223
2-41-1	1.224
2-42-1	1.223
2-43-1	1.223
2-44-1	1.223
2-45-1	1.224
2-46-1	1.224
2-47-1	1.224
2-48-1	1.224
2-49-1	1.224
2-50-1	1.223

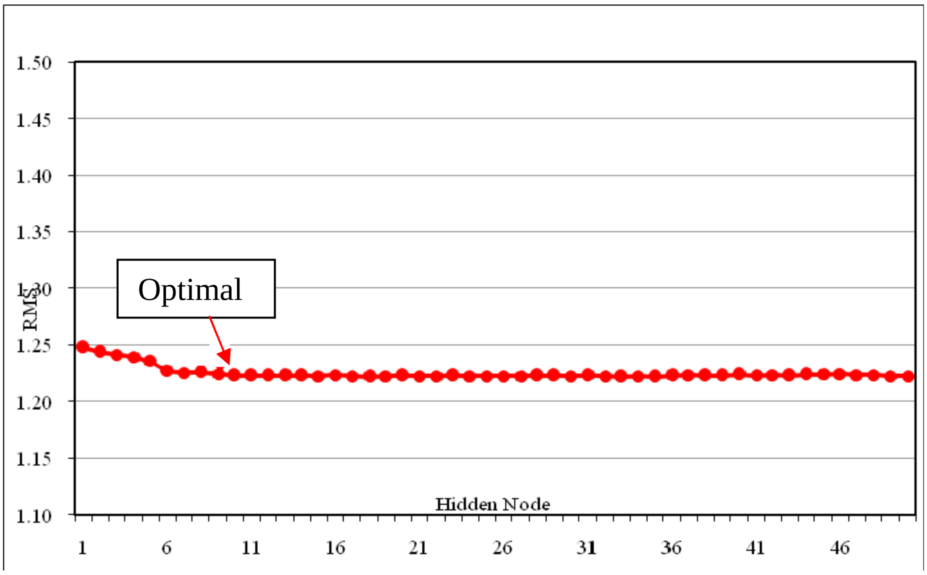


Figure 4-7 Optimum hidden layers.

Hidden node gain optimum of RMSE about 10 Node, RMSE is 1.223.

4.2.3 The First model's learning rounds

After searching hidden node, start to seek of learning rounds. The last result of model is 500 rounds. When the round of learning is increasing or decreasing that got difference accuracy of model. Therefore, the number of learning model is Hidden node 10 or the model 2-10-1 for decrease of RMSE and more accuracy of the result.

Table 4-3 RMSE from sensitivity of the first model's learning.

Learning Time	Learning RMSE	Testing RMSE
1	1.240	1.276
10	1.216	1.236
20	1.211	1.228
50	1.210	1.226
100	1.210	1.224
200	1.210	1.224
500	***1.210***	***1.223***
1000	1.210	1.223
2000	1.210	1.223
5000	1.210	1.223
10000	1.210	1.223

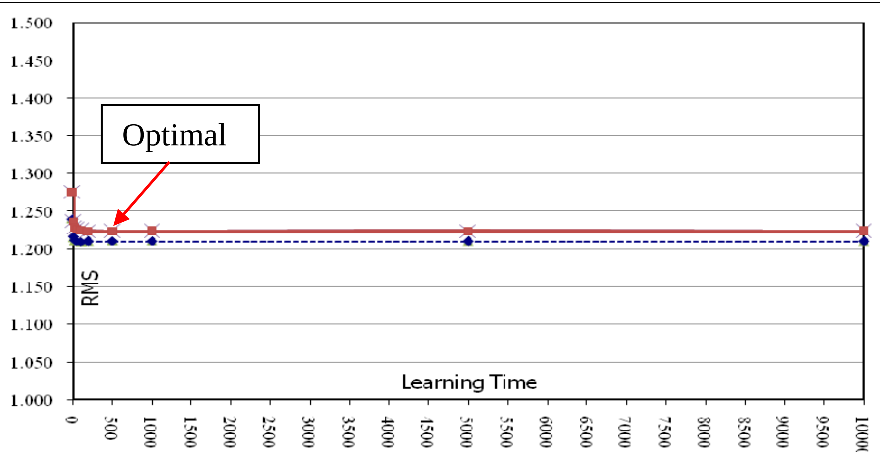


Figure 4-8 Optimum learning time.

The result of searching learning round is 500. When compare learning round and RMSE. Learning round is increasing, RMSE is lower decreasing. Therefore, to increase round is useless.

4.2.4 The First model's learning rate and momentum

After searching Hidden node and learning round, start to search learning rate and momentum. The result of program of learning rate is 0.3 and momentum is 0.2. Therefore, using the test of model 2-10-1, learning round is 500 to discover minimum RMSE.

Table 4.4 RMSE from the first model's learning rate and momentum**.**

Learning rate	Momentum	RMSE
0.1	***0.1***	***1.1476***
0.1	0.2	1.1506
0.1	0.3	1.1544
0.1	0.5	1.1664
0.1	0.9	1.3222
0.2	0.1	1.1773
0.2	0.2	1.1831
0.2	0.3	1.1911
0.2	0.5	1.2177
0.2	0.9	1.5192
0.3	0.1	1.2128
0.3	0.2	1.2231
0.3	0.3	1.2359
0.3	0.5	1.2761
0.3	0.9	1.7950
0.5	0.1	1.3023
0.5	0.2	1.3192
0.5	0.3	1.3407
0.5	0.5	1.4028
0.5	0.9	2.0734
0.9	0.1	1.5464
0.9	0.2	1.5764
0.9	0.3	1.6127
0.9	0.5	1.7496
0.9	0.9	2.7672

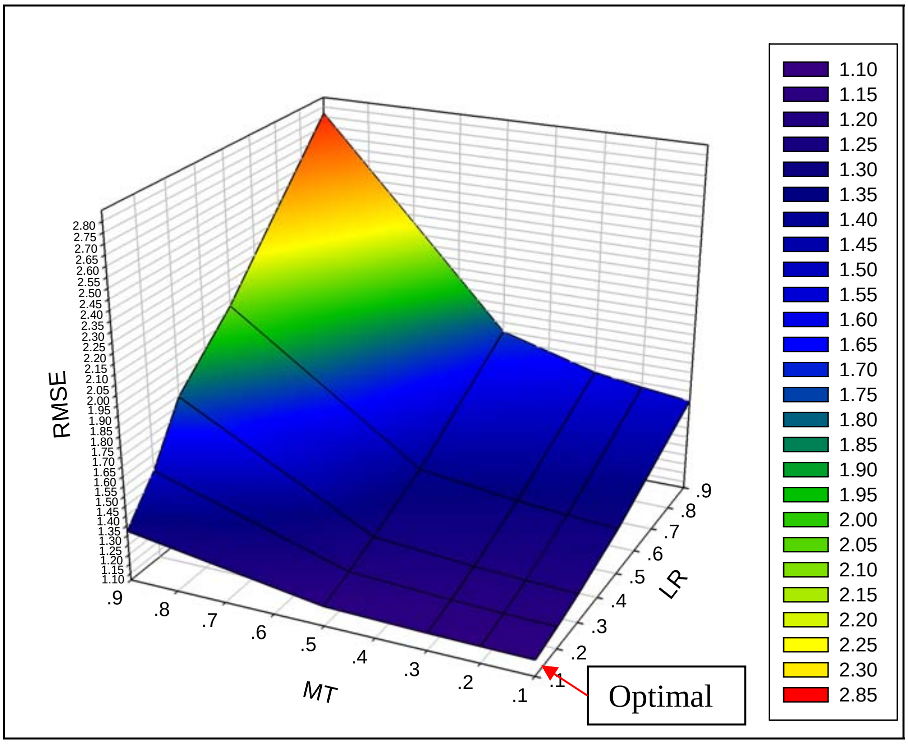


Figure 4-9 Optimum learning rate and momentum**.**

The optimum learning rate and momentum is 0.1. In the last process of architecture is 2-10-1, learning time 500, learning rate and momentum 0.1 and RMSE is 1.1476. The result of second experiment in setting up second model will prone, whether better result can be acquired. Aims to get RMSE lower than 1.1476. The model that give lower RMSE will be selected for final analysis.

4.2.5 Choose variable for the second model

All of variable, are used for the second model because the result will be compare with the result from the first model.

4.2.6 The Second model's hidden node

Searching the second model's hidden node are test 1 to 50 hidden node.

Table 4-5 Architectures of the tested Neural Networks the second model.

Network architecture	RMSE	Network architecture	RMSE
6-1-1	1.15557	6-26-1	1.11753
6-2-1	1.16137	6-27-1	1.11811
6-3-1	1.15103	6-28-1	1.11883
6-4-1	1.14157	6-29-1	1.11903
6-5-1	1.13418	6-30-1	1.11714
6-6-1	1.12501	6-31-1	1.11755
6-7-1	1.12713	6-32-1	1.11834
6-8-1	1.11986	6-33-1	1.11718
6-9-1	1.11889	***6-34-1***	***1.11651***
6-10-1	1.11847	6-35-1	1.11786
6-11-1	1.11979	6-36-1	1.11741
6-12-1	1.12180	6-37-1	1.11755
6-13-1	1.11944	6-38-1	1.11721
6-14-1	1.11835	6-39-1	1.11816
6-15-1	1.11999	6-40-1	1.11837
6-16-1	1.11853	6-41-1	1.11824
6-17-1	1.11750	6-42-1	1.11816
6-18-1	1.11971	6-43-1	1.11895
6-19-1	1.11971	6-44-1	1.11853
6-20-1	1.11773	6-45-1	1.11801
6-21-1	1.11832	6-46-1	1.11772
6-22-1	1.11694	6-47-1	1.11944
6-23-1	1.11794	6-48-1	1.11926
6-24-1	1.11701	6-49-1	1.11851
6-25-1	1.11664	6-50-1	1.11839

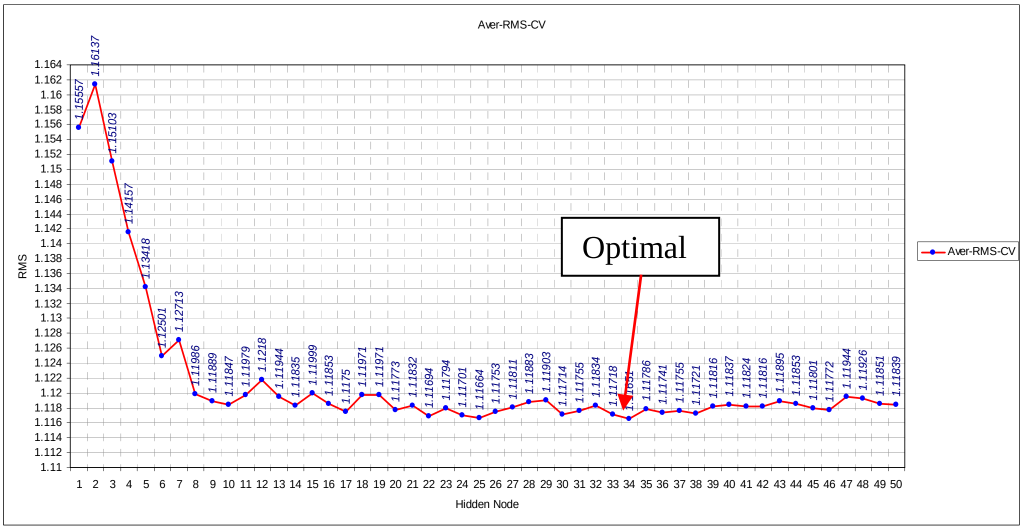


Figure 4-10 Optimum of hidden layer the second model.

Hidden node making the minimum RMSE, the amount of Hidden node is 34 and RMSE is 1.11651.

4.2.7 The Second model's learning round

After searching Hidden node, start to seek learning round which the last result of model at 500 rounds. Increasing and decreasing of the model gain the different accuracy result, therefore, the method to seek learning round amount of Hidden node 34 and form of model at 6-34-1 to gain the model of minimum RMSE which accuracy model.

Table 4-6 RMSE from sensitivity model learning the second model.

Learning Time	Learning RMSE	Testing RMSE
1	1.15863	1.23189
10	1.11708	1.14586
20	1.11261	1.13890
50	1.10500	1.13047
100	1.10225	1.12548
200	1.09658	1.12107
500	1.09292	1.11651
1000	1.09174	1.11415
2000	***1.08962***	***1.11137***
5000	1.08880	1.11068
10000	1.08831	1.10996

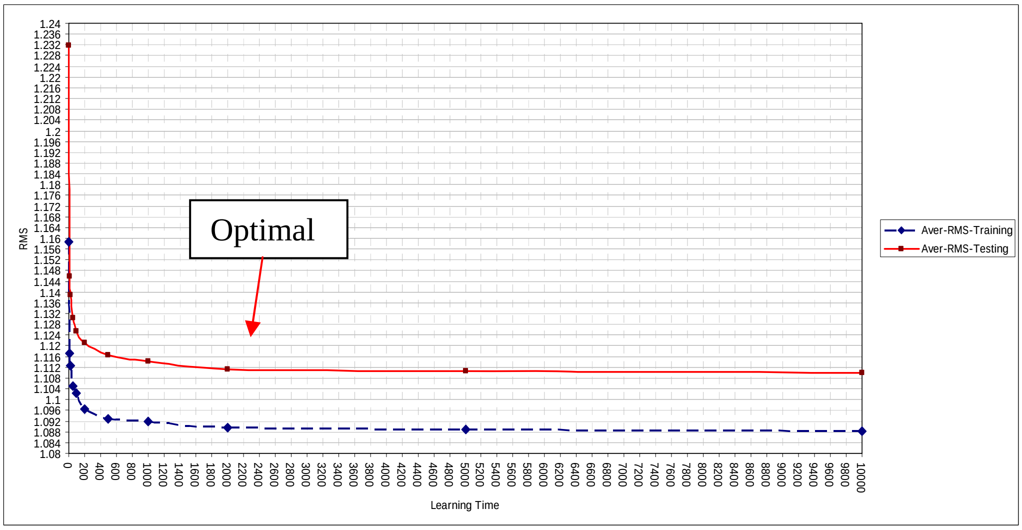


Figure 4-11 Optimum learning time the second model.

The result of learning round is 2000. Comparing of increase learning round, the result is RMSE will intense decrease. Change is insignificant.

4.2.8 The Second model's learning rate and momentum

After searching Hidden node and learning round, start to search learning rate and momentum. Learning rate is 0.3 and momentum is 0.2. Therefore, the method to search the model at 6-34-1, the round learning is 2000 to optimum RMSE.

Table 4-7 RMSE from learning rate and momentum the second model.

Learning rate	Momentum	RMSE
0.1	***0.1***	***1.05361***
0.1	0.2	1.05594
0.1	0.3	1.05930
0.1	0.5	1.07190
0.1	0.9	1.20035
0.2	0.1	1.07702
0.2	0.2	1.08232
0.2	0.3	1.08907
0.2	0.5	1.11327
0.2	0.9	1.45597
0.3	0.1	1.10419
0.3	0.2	1.11137
0.3	0.3	1.12278
0.3	0.5	1.16093
0.3	0.9	1.66665
0.5	0.1	1.18177
0.5	0.2	1.19686
0.5	0.3	1.21535
0.5	0.5	1.26900
0.5	0.9	2.48919
0.9	0.1	1.75543
0.9	0.2	1.82286
0.9	0.3	1.88488
0.9	0.5	2.10641
0.9	0.9	3.20681

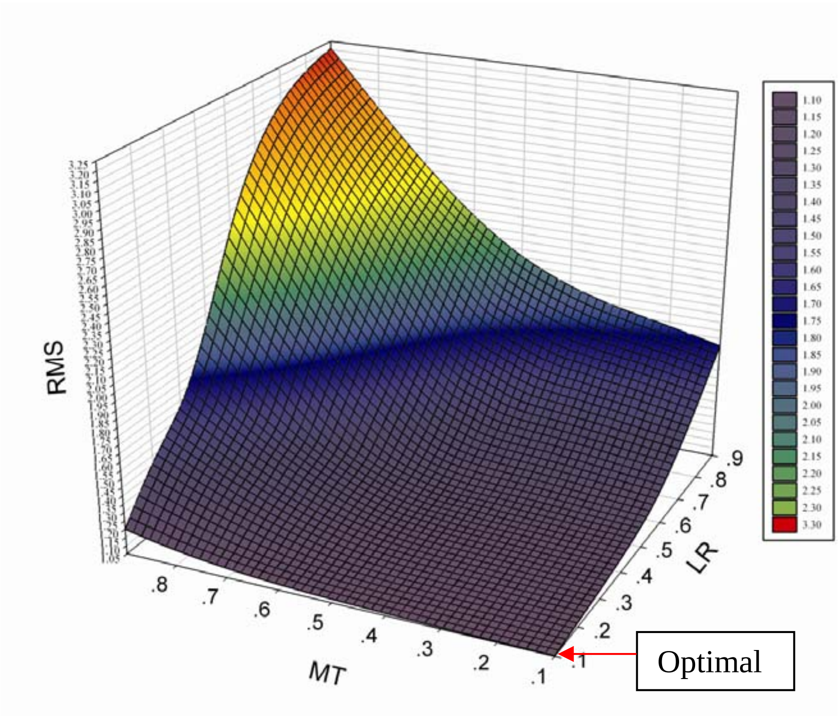


Figure 4-12 Optimum learning rate and momentum the second model

Searching learning value and stimulate learning value model. The best result of learning value and stimulate learning value is 0.1. In the last process of the model is model 6-34-1, learning time 2000, learning rate and momentum is 0.1 and RMSE is 1.05361.

4.2.9 Compare between the first model and the second model

The result from the second model is better than the first model because RMSE is lesser (1.05631 and 1.1476).

4.2.10 Check the accuracy and reliability of the second model

To create ten of models, start Random Seed 0 to Random Seed 9. Then, using each model to gain the average of RMSE for accurate and accuracy variable.

Table 4-8 Value RMSE and R square of ANNs model.

Random Seed	RMSE	R	R square
0	1.0264	0.7388	0.533107409
1	1.0261	0.7402	0.519693371
2	1.0344	0.7405	0.534118901
3	1.0282	0.7401	0.522098091
4	1.1324	0.7399	0.516586858
5	1.0242	0.7399	0.513423329
6	1.0252	0.7407	0.534853586
7	1.0272	0.7395	0.510917929
8	1.0552	0.7402	0.517776772
9	1.0241	0.7401	0.527065982
average	***1.04034***	***0.73999***	***0.522964223***

4.3 Compare between ANNs model and Modified Penman equation

Comparison between result from ANNs model and Modified Penman equation using random 10% data from validate data of use validate model.

Table 4-9 ET_o calculate from Modified Penman and ANNs model, difference Modified Penman and ANNs model with actual ET_o**.**

No.	ET_o PENMAN	ET_o actual	ET_o ANNs	Difference ANNs-actual	Difference PENMAN-actual
1	4	5.27	1.3878	-3.8822	-1.27
2	4.4	5.015	2.2541	-2.7609	-0.615
3	4.55	2.635	2.0782	-0.5568	1.915
4	5.99	5.355	1.2986	-4.0564	0.635
5	4.82	2.635	1.7606	-0.8744	2.185
6	5.44	4.505	1.7696	-2.7354	0.935
7	4.83	5.865	3.6016	-2.2634	-1.035
8	5.72	3.315	2.9627	-0.3523	2.405
9	5.37	3.06	2.2925	-0.7675	2.31
10	5.65	4.59	2.4562	-2.1338	1.06
11	5.68	7.565	3.7188	-3.8462	-1.885
12	4.16	2.975	3.7581	0.7831	1.185
13	5	3.825	2.4843	-1.3407	1.175
14	5.27	3.57	1.6032	-1.9668	1.7
15	4.48	2.21	2.7163	0.5063	2.27
16	4.49	3.655	3.2201	-0.4349	0.835
17	3.94	3.4	1.7603	-1.6397	0.54
18	4.99	3.145	1.4863	-1.6587	1.845
19	6.93	8.075	1.2002	-6.8748	-1.145
20	5.95	3.06	2.2217	-0.8383	2.89
21	6.78	3.995	1.6285	-2.3665	2.785
22	5.12	6.375	2.1538	-4.2212	-1.255
23	3.48	3.145	2.829	-0.316	0.335
24	4.3	2.72	2.8748	0.1548	1.58
25	4.99	7.565	2.3732	-5.1918	-2.575
26	2.9	5.61	2.6772	-2.9328	-2.71
27	6.35	3.485	2.5624	-0.9226	2.865
28	5.43	1.36	2.1165	0.7565	4.07
29	4.85	3.57	2.2816	-1.2884	1.28
30	2.86	1.53	2.7847	1.2547	1.33
31	3.39	1.53	3.2856	1.7556	1.86
32	6.61	3.23	2.5368	-0.6932	3.38
33	5.97	5.44	1.7391	-3.7009	0.53
34	6.36	1.955	1.7746	-0.1804	4.405
35	5.29	5.695	2.8142	-2.8808	-0.405
36	5.91	4.165	2.0684	-2.0966	1.745
37	6.21	2.465	2.4946	0.0296	3.745
38	6.48	2.72	2.6053	-0.1147	3.76
39	6.85	5.95	3.4262	-2.5238	0.9
40	4.52	3.485	3.89	0.405	1.035
41	6.8	4.25	3.762	-0.488	2.55
42	6.01	2.125	1.2556	-0.8694	3.885
43	7.33	5.355	2.6819	-2.6731	1.975
44	7.14	4.59	3.9527	-0.6373	2.55
45	6.85	3.74	2.1838	-1.5562	3.11
46	5.43	2.38	3.1168	0.7368	3.05
47	5.35	4.25	2.7218	-1.5282	1.1
48	4.47	3.825	2.8497	-0.9753	0.645
49	5.08	3.315	3.2042	-0.1108	1.765
50	5.19	3.145	3.4761	0.3311	2.045
51	6.28	3.315	4.5413	1.2263	2.965
52	7.08	4.42	4.5477	0.1277	2.66
53	6.33	3.23	4.7667	1.5367	3.1
54	7.08	2.89	4.7906	1.9006	4.19
55	7.85	5.44	3.1703	-2.2697	2.41
56	7.01	3.995	1.902	-2.093	3.015
57	7.4	4.08	1.3655	-2.7145	3.32
58	4.63	1.785	2.1575	0.3725	2.845
59	5.28	4.505	3.2244	-1.2806	0.775
60	6.61	4.335	4.2406	-0.0944	2.275
61	6.31	5.61	3.7323	-1.8777	0.7
62	6.47	2.805	3.4554	0.6504	3.665
63	6.4	4.76	4.2929	-0.4671	1.64

No.	ET_o PENMAN	ET_o actual	ET_o ANNs	Difference ANNs-actual	Difference PENMAN-actual
64	7.24	5.355	4.6679	-0.6871	1.885
65	7.25	3.315	4.149	0.834	3.935
66	6.04	3.57	3.4898	-0.0802	2.47
67	7.12	2.975	4.797	1.822	4.145
68	7.21	4.845	3.4642	-1.3808	2.365
69	7.41	3.74	4.6613	0.9213	3.67
70	7.79	3.74	3.9867	0.2467	4.05
71	6.6	4.675	3.0545	-1.6205	1.925
72	5.94	4.42	2.9742	-1.4458	1.52
73	6.03	4.08	2.5352	-1.5448	1.95
74	6.63	3.23	4.4254	1.1954	3.4
75	4.67	2.89	3.5109	0.6209	1.78
76	5.15	3.145	4.0482	0.9032	2.005
77	6.32	5.1	3.6804	-1.4196	1.22
78	6.47	1.7	3.5542	1.8542	4.77
79	6.4	5.525	2.7604	-2.7646	0.875
80	7.12	3.825	4.5772	0.7522	3.295
81	7.23	3.825	3.9114	0.0864	3.405
82	6.93	3.4	3.5676	0.1676	3.53
83	7.18	5.185	2.6522	-2.5328	1.995
84	6.74	3.655	3.7114	0.0564	3.085
85	6.9	4.93	4.478	-0.452	1.97
86	7.26	3.4	4.9141	1.5141	3.86
87	7.39	4.675	1.7319	-2.9431	2.715
88	7.28	5.27	2.2086	-3.0614	2.01
89	7.15	4.93	2.2738	-2.6562	2.22
90	7.34	2.55	2.5848	0.0348	4.79
91	6.3	5.185	2.2296	-2.9554	1.115
92	7.09	3.57	2.6402	-0.9298	3.52
93	7.46	4.25	2.2012	-2.0488	3.21
94	6.52	2.38	2.6972	0.3172	4.14
95	5.71	5.1	4.3925	-0.7075	0.61
96	6.15	3.825	4.1304	0.3054	2.325
97	5.97	3.655	3.2264	-0.4286	2.315
98	5.79	2.635	3.4137	0.7787	3.155
99	3.92	1.955	4.3446	2.3896	1.965
100	5.3	3.06	4.5849	1.5249	2.24
AVERAGE	**5.9369**	**3.91425**	**3.025705**	**-0.888545**	**2.02265**

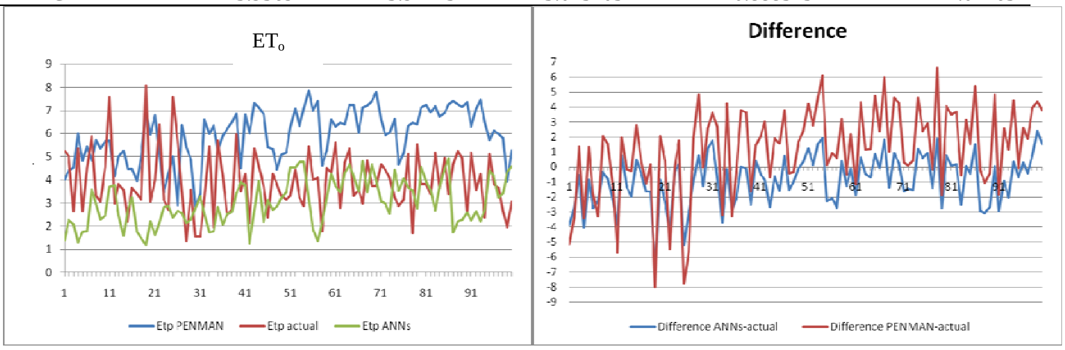


Figure 4-13 Comparison ET_o from Modified Penman, ANNs model and actual ET_o**.**

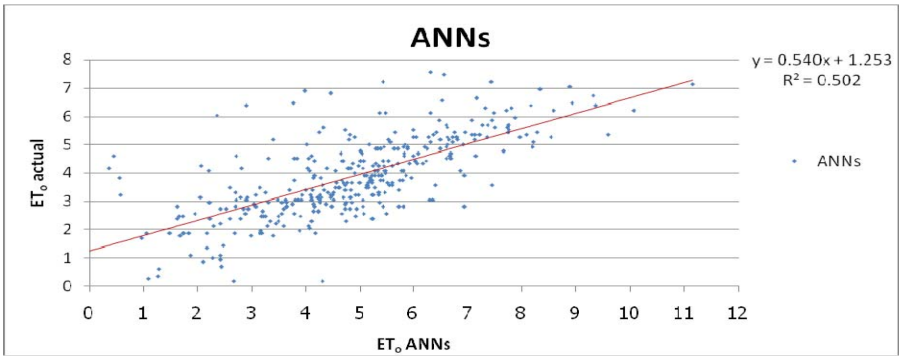


Figure 4-14 Correlation of ANNs model and actual ET_o (R = 0.709).

As the comparison result of ANNs model and actual ET_o is 46% (RMSE = 1.915). However, Modified Penman equation and actual ET_o is 51% (RMSE = 2.537), therefore, result from ANNs model is better than Modified Penman equation.

For the correlation testing between ET_o actual values and ET_o obtained by ANNs model, it is found that with daily sampling values 365 days, the R values is 0.709 as show in Figure 4-14.

4.4 Estimate evapotranspiration on climate pattern under 3 difference climate scenarios

4.4.1 Using the projected daily climate data under three different climate scenarios. The selected concentrations represent the present, the middle of century, and the end of century (the data were received from SEA START RC). The data, which is daily data, will be grouped together into monthly. The variables includes:

- maximum temperature
- minimum temperature
- humidity
- maximum wind speed
- solar radiation

Input climate variable to ANNs model (the second model) for compute estimation evapotranspiration value.

4.5 Maps ET_o on climate scenario 1, climate scenario 2 and climate scenario 3

4.5.1 Result estimate ET_o from data climate scenario 1, climate scenario 2 and climate scenario 3 is point value on 3 climate scenarios (Table 4-10), so the ET_o map will interpolate ET_o value in study area using ARCGIS (Figure 4-15 to Figure 4-26).

Table 4-10 Result estimate ET_o and % difference ET_o from climate scenario 1, climate scenario 2 and climate scenario 3 in 5 regions.

Region	Northern	Difference baseline(%)	Northeastern	Difference baseline (%)	Central, Eastern and Western	Difference baseline (%)
January	3.04		3.707		3.923	
ET 540	2.334	-23.23	2.696	-27.28	2.866	-26.957
ET 720	3.501	15.14	4.172	12.542	4.426	12.819
February	4.005		4.13		4.291	

Region	Northern	Difference baseline (%)	Northeastern	Difference baseline (%)	Central, Eastern and Western	Difference baseline (%)
ET 540	3.731	-6.84	3.874	-6.193	4.215	-1.789
ET 720	3.866	-3.475	4.263	3.238	4.547	5.966
March	5.132		5.007		5.047	
ET 540	4.819	-6.092	4.867	-2.81	5.171	2.447
ET 720	5.175	0.842	5.502	9.88	5.638	11.706
April	5.633		5.427		5.283	
ET 540	5.079	-9.83	4.221	-22.223	5.072	-3.987
ET 720	5.482	-2.676	4.976	-8.309	5.619	6.363
May	4.771		4.564		4.686	
ET 540	3.92	-17.83	3.335	-26.916	4.298	-8.281
ET 720	4.915	3.036	4.365	-4.353	5.53	18.005
June	3.742		4.014		4.201	
ET 540	3.364	-10.093	3.764	-6.211	3.942	-6.182
ET 720	4.363	16.606	4.67	16.366	4.641	10.471
July	3.554		4.047		4.187	
ET 540	3.117	-12.292	3.545	-12.404	3.713	-11.324
ET 720	3.374	-5.066	3.843	-5.021	4.18	-0.172
August	3.372		3.56		4.05	
ET 540	3.038	-9.897	3.376	-5.162	3.562	-12.053
ET 720	3.071	-8.939	3.358	-5.663	4.051	0.023
September	3.292		3.485		3.7	
ET 540	2.695	-18.142	2.979	-14.538	3.066	-17.131
ET 720	2.895	-12.041	3.186	-8.583	3.609	-2.453
October	3.067		3.409		3.386	
ET 540	2.746	-10.47	3.211	-5.808	3.06	-9.633
ET 720	2.927	-4.579	3.158	-7.385	3.3	-2.557
November	2.771		3.625		3.593	
ET 540	2.373	-14.345	3.277	-9.603	3.58	-0.353
ET 720	2.684	-3.143	3.436	-5.206	3.867	7.611
December	2.678		3.507		3.872	
ET 540	2.238	-16.432	3.12	-11.041	3.426	-11.502
ET 720	2.324	-13.243	3.266	-6.893	3.702	-4.39

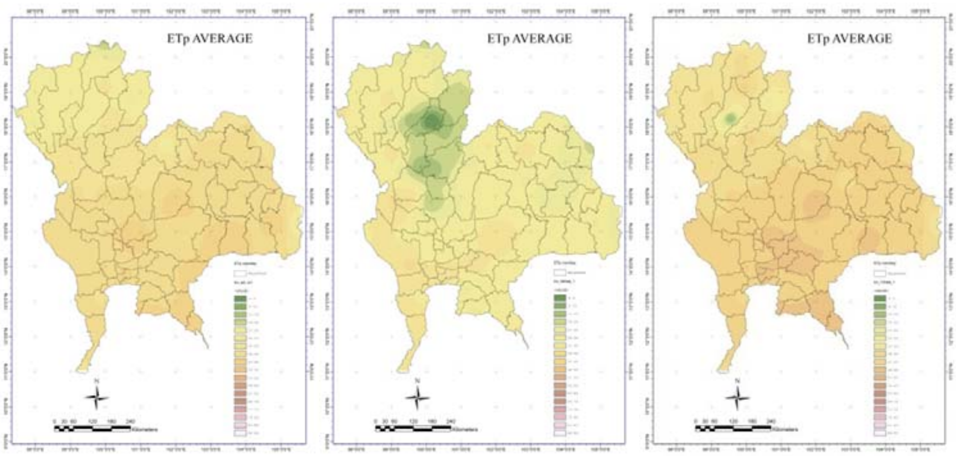


Figure 4-15 ET_o map from climate scenario 1, climate scenario 2 and climate scenario 3 on January**.**

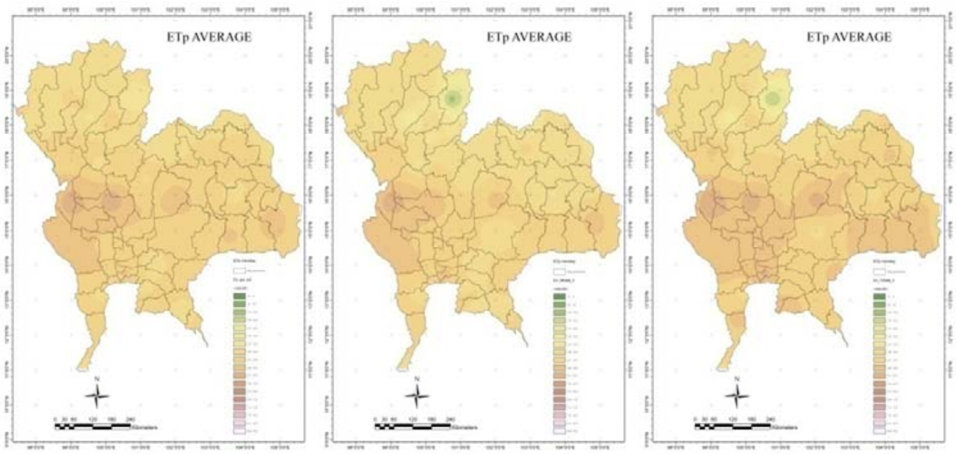


Figure 4-16 ET$_o$ map from climate scenario 1, climate scenario 2 and climate scenario 3 on February**.**

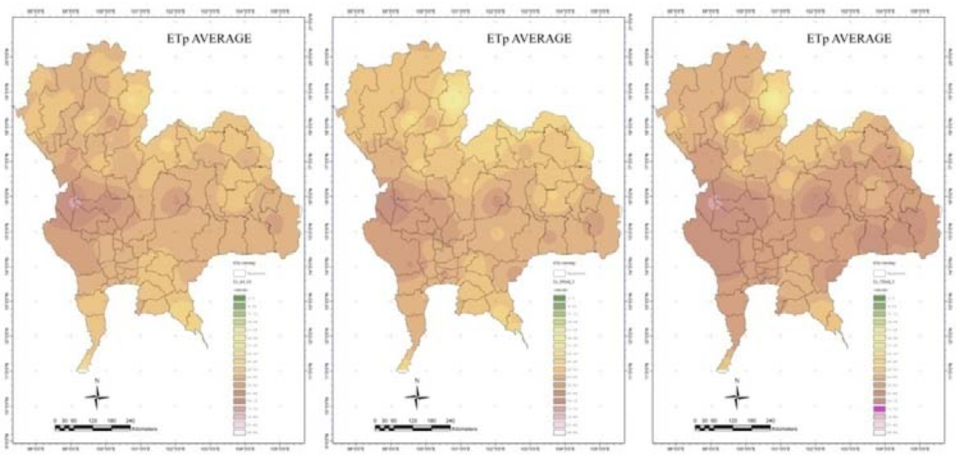


Figure 4-17 ET$_o$ map from climate scenario 1, climate scenario 2 and climate scenario 3 on March**.**

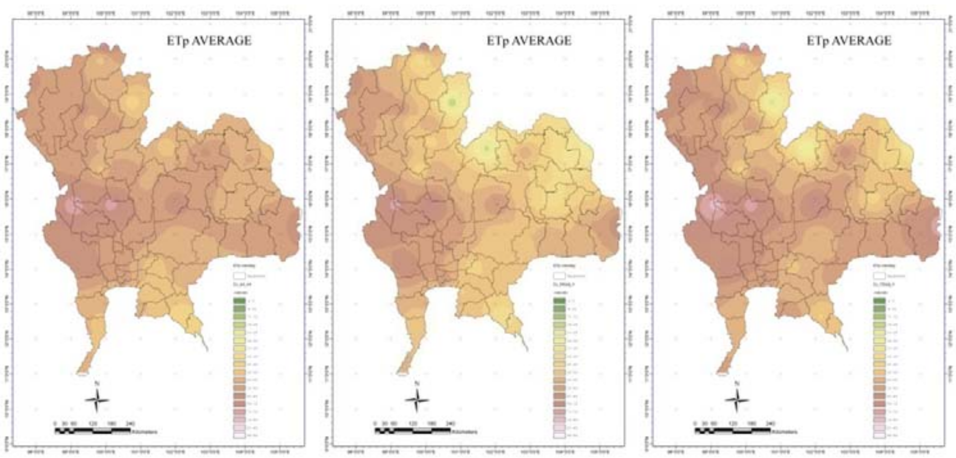


Figure 4-18 ET$_o$ map from climate scenario 1, climate scenario 2 and climate scenario 3 on April**.**

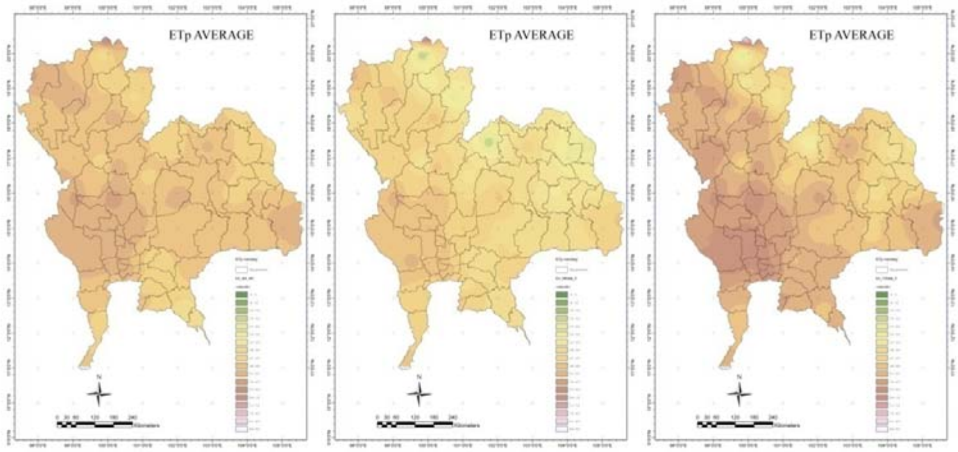


Figure 4-19 ET$_o$ map from climate scenario 1, climate scenario 2 and climate scenario 3 on May**.**

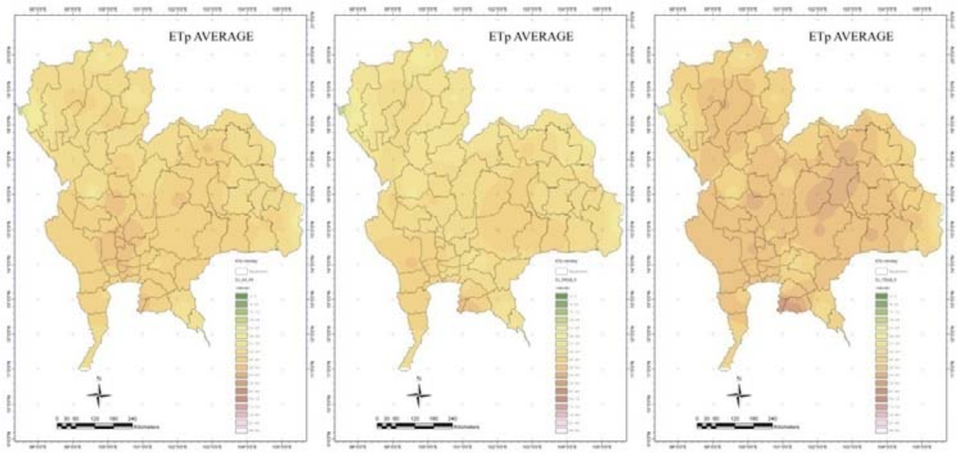


Figure 4-20 ET$_o$ map from climate scenario 1, climate scenario 2 and climate scenario 3 on June**.**

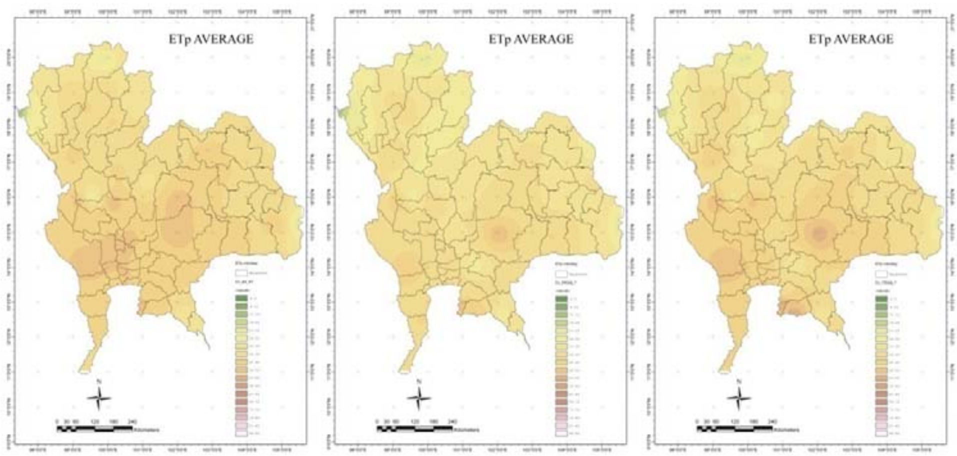


Figure 4-21 ET$_o$ map from climate scenario 1, climate scenario 2 and climate scenario 3 on July**.**

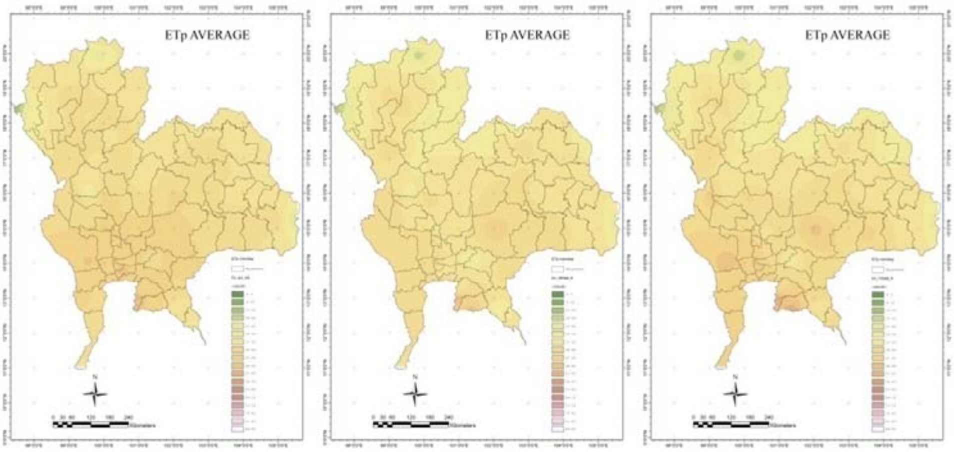


Figure 4-22 ET$_o$ map from climate scenario 1, climate scenario 2 and climate scenario 3 on August**.**

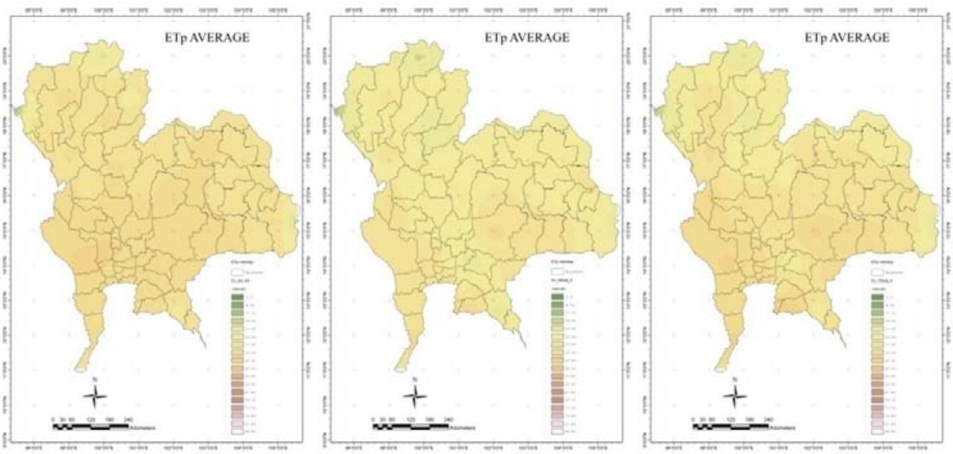


Figure 4-23 ET$_o$ map from climate scenario 1, climate scenario 2 and climate scenario 3 on September**.**

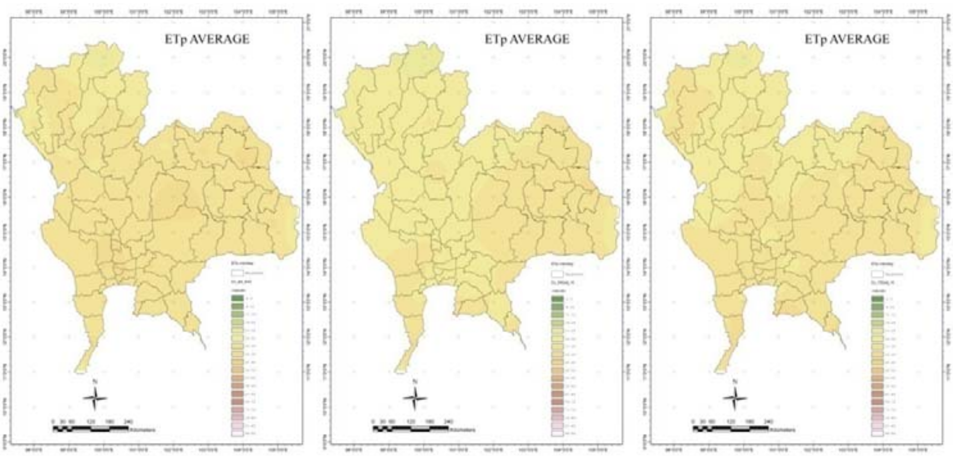


Figure 4-24 ET$_o$ map from climate scenario 1, climate scenario 2 and climate scenario 3 on October**.**

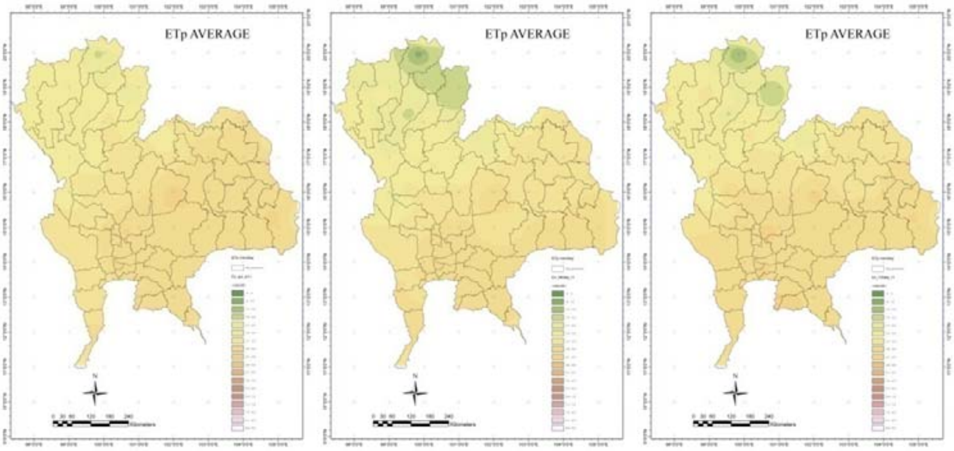


Figure 4-25 ET_o map from climate scenario 1, climate scenario 2 and climate scenario 3 on November**.**

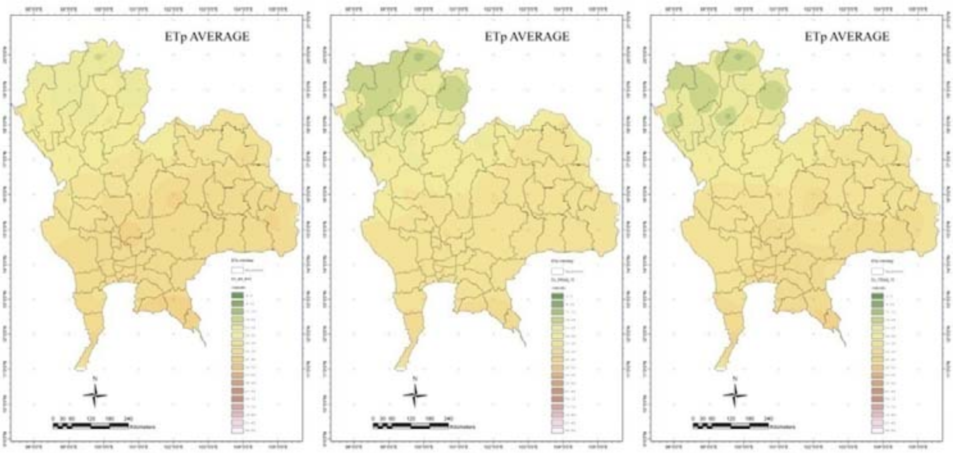


Figure 4-26 ET_o map from climate scenario 1, climate scenario 2 and climate scenario 3 on December.

It is found that the best ANN architectural layer is six, thirty four, and one neuron (6-34-1) in the input, hidden, and output layers with 2000 antennary for learning time and with 0.1 and 0.1 learning rate and momentum.

Results show the decreasing trend of ET_o in the future under future climate condition when CO_2 concentration is 540 ppm (climate scenario 2) ET_o will decrease about 26 % on January, 5 % on February, 2 % on March, 12 % on April, 18 % on May, 7 % on June, 12 % on July, 9 % on August, 17 % on September, 9 % on October, 8 % on November and 13 % on December (in climate scenario 2 ET_o decrease because precipitation and humidity are increase).

But in the longer term toward the end of 21st century, the climate condition under CO_2 concentration 720 ppm (climate scenario 3), shows fluctuation of ET_o over the year when compare to the baseline period. ET_o will increasing up to 14 % on January, 2 % on February, 8 % on March, 5 % on May, 15 % on June, meanwhile ET_o will decrease 2 % on April, 3 % on July, 5 % on August, 8 % on September, 5 % on October, and 8 % on December (in climate scenario 3 ET_o decrease because precipitation and humidity are unstable).

4.6 ET paddy map on climate scenario 1, climate scenario 2 and climate scenario 3

ET paddy compute from ET_o data multiply by paddy factor during paddy grow (Table 4-11). The result of ET paddy show in map on 3 climate scenarios and difference ET paddy map when climate change (Figure 4-27 to Figure 4-36).

Table 4-11 Result estimate ET paddy and % difference ET paddy from data on climate scenario 1, climate scenario 2 and climate scenario 3 in 5 regions.

Region	Northern	Difference baseline (%)	Northeastern	Difference baseline (%)	Central, Eastern and Western	Difference baseline (%)
May	3.816		3.651		3.749	
ET 540	3.136	-17.830	2.668	-26.916	3.438	-8.281
ET 720	3.932	3.036	3.492	-4.353	4.424	18.005
June	4.490		4.816		5.042	
ET 540	4.037	-10.093	4.517	-6.211	4.730	-6.182
ET 720	5.235	16.606	5.605	16.366	5.570	10.471
July	4.621		5.261		5.444	
ET 540	4.053	-12.292	4.608	-12.404	4.827	-11.324
ET 720	4.387	-5.066	4.996	-5.021	5.434	-0.172
August	3.912		4.130		4.698	
ET 540	3.524	-9.897	3.917	-5.162	4.132	-12.053
ET 720	3.562	-8.939	3.896	-5.663	4.699	0.023
September	1.646		1.743		1.850	
ET 540	1.347	-18.142	1.489	-14.538	1.533	-17.131
ET 720	1.448	-12.041	1.593	-8.583	1.804	-2.453

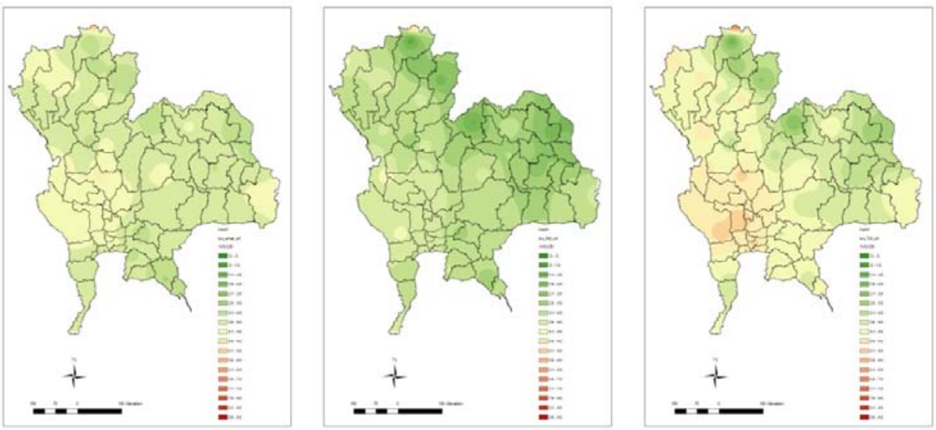


Figure 4-27 ET paddy map on climate scenario 1, climate scenario 2 and climate scenario 3 on May**.**

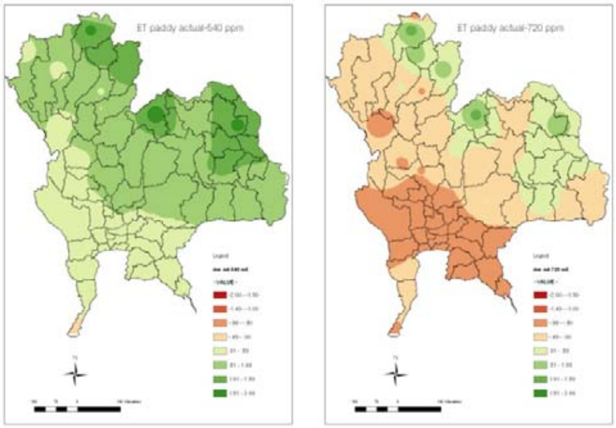


Figure 4-28 Future change in ET paddy between climate scenario 1 (baseline) and climate scenario 2 and climate scenario 3 on May**.**

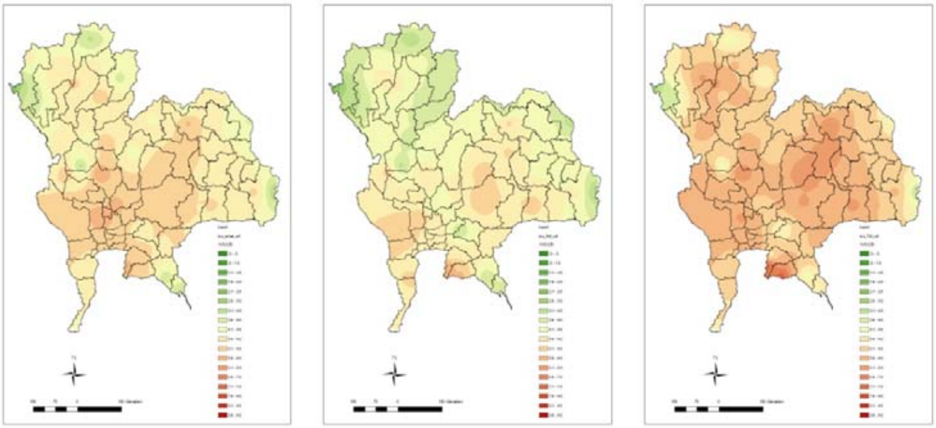


Figure 4-29 ET paddy map on climate scenario 1, climate scenario 2 and climate scenario 3 on June**.**

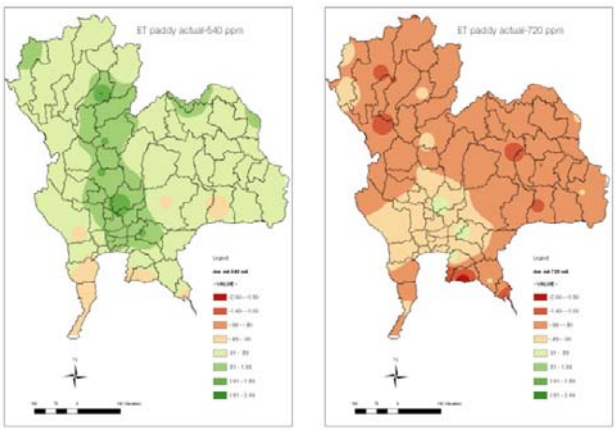


Figure 4-30 Future change in ET paddy between climate scenario 1 (baseline) and climate scenario 2 and climate scenario 3 on June**.**

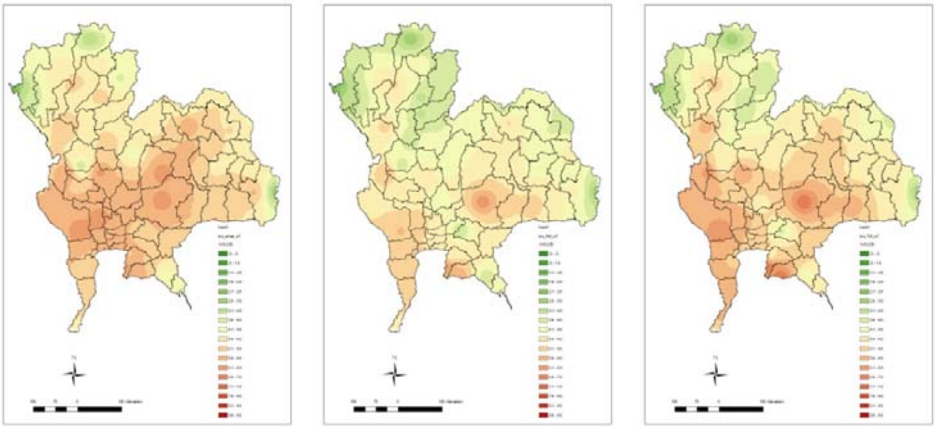


Figure 4-31 ET paddy map on climate scenario 1, climate scenario 2 and climate scenario 3 on July**.**

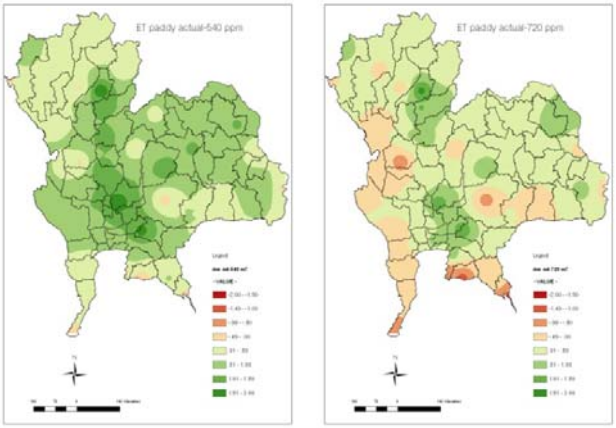


Figure 4-32 Future change in ET paddy between climate scenario 1 (baseline) and climate scenario 2 and climate scenario 3 on July**.**

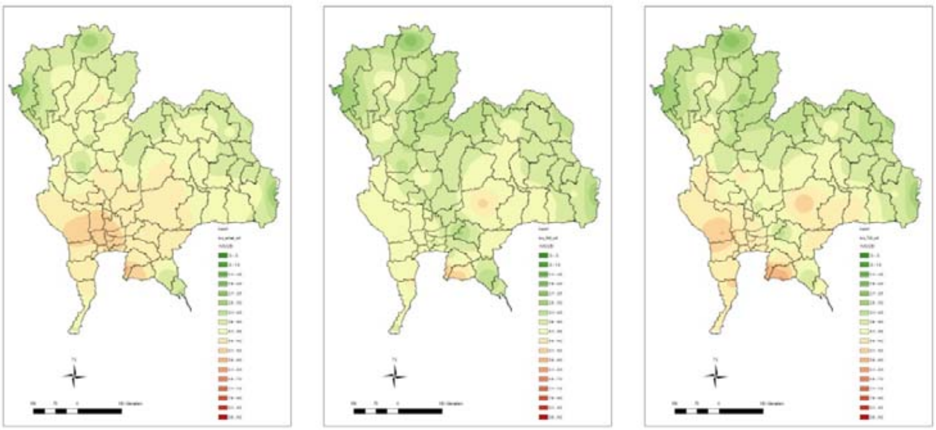


Figure 4-33 ET paddy map on climate scenario 1, climate scenario 2 and climate scenario 3 on August**.**

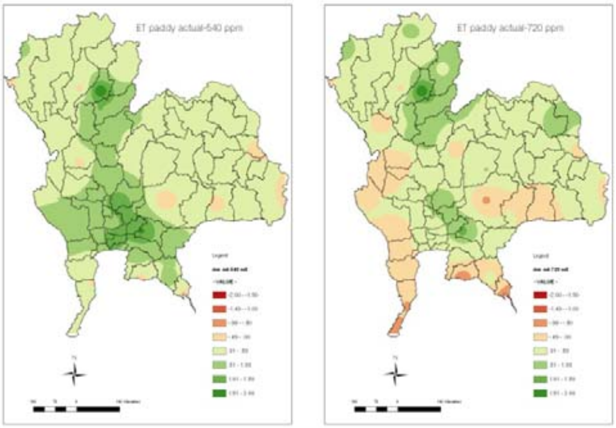


Figure 4-34 Future change in ET paddy between climate scenario 1 (baseline) and climate scenario 2 and climate scenario 3 on August**.**

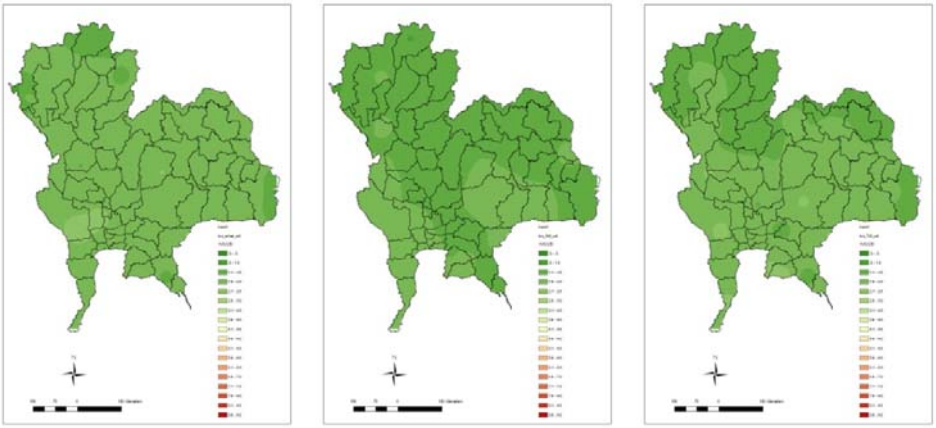


Figure 4-35 ET paddy map on climate scenario 1, climate scenario 2 and climate scenario 3 on September**.**

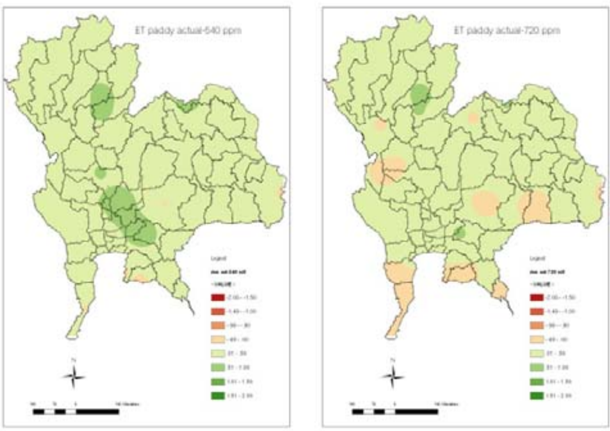


Figure 4-36 Future change in ET paddy between climate scenario 1 (baseline) and climate scenario 2 and climate scenario 3 on September**.**

After using coefficient to compare of ET paddy in the future under future climate condition when CO_2 concentration is 540 ppm (climate scenario 2) ET_o will decrease about 18 % on May, 7 % on June, 12 % on July, 9 % on August, 17 % on September. But in the climate condition under CO_2 concentration 720 ppm (climate scenario 3) ET paddy will increasing up 6 % on the first and 14 % second month meanwhile in the third to the fifth month ET paddy will decrease to 3 %, 5 %, and 8 % on respectively.

The result is show climate change that is effect to ET_o. The increasing of CO_2 in climate scenario 1, climate scenario 2 and climate scenario 3, that effect to increase and decrease of ET_o, Therefore, to prepare for climate change have to study more climate scenarios.

CHAPTER V
CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This study is the development of framework and process is to apply Data Mining technique for prediction of ET_o base on difference climate using ANNs model for analysis tools. Then, to conclude changing of ET_o under climate change phenomenon. This study found that the best ANN architectural layer is six, thirty four, and one neuron (6-34-1) in the input, hidden, and output layers with 2000 antennary for learning time and with 0.1 and 0.1 learning rate and momentum.

Results show the decreasing trend of ET_o in the future under future climate condition when CO_2 concentration is 540 ppm (climate scenario 2) ET_o will decrease about 26 % in January, 5 % in February, 2 % in March, 12 % in April, 18 % in May, 7 % in June, 12 % in July, 9 % in August, 17 % in September, 9 % in October, 8 % in November and 13 % in December.

But in the longer term toward the end of 21st century, the climate condition under CO_2 concentration 720 ppm (climate scenario 3), shows fluctuation of ET_o over the year when compare to the baseline period. ET_o will increasing up to 14 % in January, 2 % in February, 8 % in March, 5 % in May, 15 % in June, meanwhile ET_o will decrease 2 % in April, 3 % in July, 5 % in August, 8 % in September, 5 % in October, and 8 % in December**.**

After using coefficient to compare of ET paddy in the future under future climate condition when CO_2 concentration is 540 ppm (climate scenario 2) ET_o will decrease about 18 % in May, 7 % in June, 12 % in July, 9 % in August, 17 % in September. But in the climate condition under CO_2 concentration 720 ppm (climate scenario 3) ET paddy will increasing up 6 % in the first and 14 % second month meanwhile in the third to the fifth months ET paddy will decrease to 3 %, 5 % and 8 % on respectively.

The framework set up under this study can be used for analysis future change in ET using new climate scenario that may be developed in the future.

5.2 Recommendations

1. The data mining using observer climate data but Thailand does not have enough and continue data for a long time. Therefore, the model will be has limitation.
2. To get better understanding of future ET in Thailand under climate change in fecund, additional climate scenario are required to use in the analysis to get diverse result.
3. This data mining can use climate data from others multiple climate scenarios to prediction ET_o and can be analysis to comparison ET_o.
4. To must be compare ANNs model with actual ET_o and PENMAN equation in more case (other climate data) for increase reliability.

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In Thai

กรมพัฒนาพลังงานทดแทนและอนุรักษ์พลังงาน กระทรวงพลังงานร่วมกับภาควิชาฟิสิกส์ คณะวิทยาศาสตร์ มหาวิทยาลัยศิลปากร. (2548). *คู่มือข้อมูลมาตรฐาน ภูมิอากาศและแสงอาทิตย์สำหรับใช้งานในด้านพลังงานทดแทน*. กรุงเทพมหานคร: ภาควิชาฟิสิกส์ มหาวิทยาลัยศิลปากร.

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APPENDIX

APPENDIX A
RAW DATA

Main Meteorology data attach in CD1.

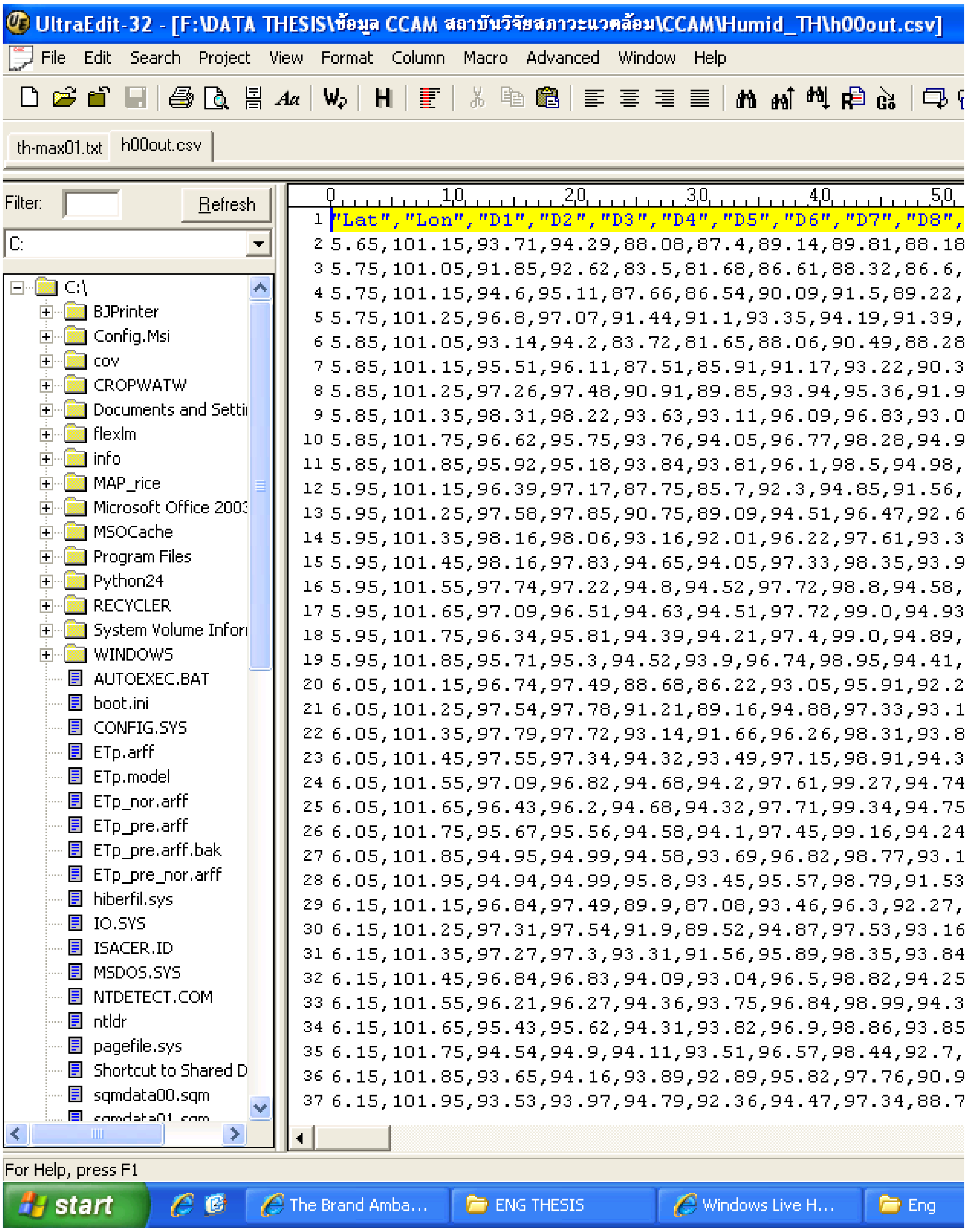
Main CCAM data attach in CD2 and CD3.

Sample data 7 variables from 118,741 data use compute Data Mining.

stn_name	stncode	year	dday	month	maxtmp	mintmp	avgrh	windmax	solar	evapotran
Bangkok Metropolis*	455201	1982	1	1	33.5	21.7	74	6	156.7	3.655
Bangkok Metropolis*	455201	1982	2	1	31.8	22.8	77	8	126.65	2.720
Bangkok Metropolis*	455201	1982	3	1	32.2	22.4	77	8	140.86	3.230
Bangkok Metropolis*	455201	1982	4	1	32	21.8	78	6	142.41	3.910
Bangkok Metropolis*	455201	1982	5	1	32.5	20.9	71	14	159.64	2.975
Bangkok Metropolis*	455201	1982	6	1	32.7	20.6	70	10	171.18	3.400
Bangkok Metropolis*	455201	1982	7	1	31.1	21.3	65	14	170.54	4.250
Bangkok Metropolis*	455201	1982	8	1	30.5	20	64	8	166.63	5.610
Bangkok Metropolis*	455201	1982	9	1	30.2	18.6	65	10	180.38	4.590
Bangkok Metropolis*	455201	1982	10	1	31.5	16.3	67	9	164.75	2.210
Bangkok Metropolis*	455201	1982	11	1	31.8	18	71	10	172.6	3.400
Bangkok Metropolis*	455201	1982	12	1	32.4	19.5	74	8	150.98	3.740
Bangkok Metropolis*	455201	1982	13	1	32.5	19.5	73	6	159.89	3.230
Bangkok Metropolis*	455201	1982	14	1	33.2	20	71	5	162.07	2.975
Bangkok Metropolis*	455201	1982	15	1	32.3	21.6	61	16	172.3	3.655
Bangkok Metropolis*	455201	1982	16	1	31.8	21.6	65	11	138.53	4.505
Bangkok Metropolis*	455201	1982	17	1	31.6	19.9	67	14	169.34	4.420
Bangkok Metropolis*	455201	1982	18	1	31.3	20.8	64	18	170.35	3.995
Bangkok Metropolis*	455201	1982	19	1	30.3	19.4	64	14	167.75	5.185
Bangkok Metropolis*	455201	1982	20	1	31.7	18.4	63	9	161.18	4.675
Bangkok Metropolis*	455201	1982	21	1	32	19.2	64	9	153.5	4.165
Bangkok Metropolis*	455201	1982	22	1	31	19.6	71	6	164.61	4.165
Bangkok Metropolis*	455201	1982	23	1	32.5	21	76	14	159.57	2.465
Bangkok Metropolis*	455201	1982	24	1	33	21.1	76	10	168.51	3.315
Bangkok Metropolis*	455201	1982	25	1	33.5	22	74	6	160.67	4.335
Bangkok Metropolis*	455201	1982	26	1	32	21.4	64	18	169.89	4.080
Bangkok Metropolis*	455201	1982	27	1	31.3	19.7	61	12	151.06	3.910
Bangkok Metropolis*	455201	1982	28	1	31.9	19.3	66	16	174.22	4.420
Bangkok Metropolis*	455201	1982	29	1	32.1	21.4	58	16	159.89	3.910
Bangkok Metropolis*	455201	1982	30	1	32.2	20.5	61	20	168.48	5.355
Bangkok Metropolis*	455201	1982	31	1	33.3	21.1	67	16	175.2	4.845
Bangkok Metropolis*	455201	1982	1	2	33.5	22.1	63	16	167	5.100
Bangkok Metropolis*	455201	1982	2	2	33.3	23.4	67	12	166.26	4.505
Bangkok Metropolis*	455201	1982	3	2	32.2	24.3	79	12	175.52	3.655
Bangkok Metropolis*	455201	1982	4	2	32	24.4	79	16	157.62	5.270
Bangkok Metropolis*	455201	1982	5	2	32.2	24.8	78	18	173	5.015
Bangkok Metropolis*	455201	1982	6	2	32.2	25	77	20	173.26	3.655
Bangkok Metropolis*	455201	1982	7	2	31.9	25.4	77	11	175.41	4.760
Bangkok Metropolis*	455201	1982	8	2	31.4	25.2	77	19	171.13	4.165
Bangkok Metropolis*	455201	1982	9	2	32	23.3	78	16	164.74	5.100
Bangkok Metropolis*	455201	1982	10	2	32.1	23.1	76	18	147.21	3.655
Bangkok Metropolis*	455201	1982	11	2	32.8	24.6	75	16	170.44	4.760
Bangkok Metropolis*	455201	1982	12	2	33.5	23.3	75	16	154.52	3.995
Bangkok Metropolis*	455201	1982	13	2	33.3	23.7	77	16	164.09	5.100
Bangkok Metropolis*	455201	1982	14	2	34	23.9	76	15	160.44	4.250
Bangkok Metropolis*	455201	1982	15	2	31.3	24.5	78	10	158.1	4.420
Bangkok Metropolis*	455201	1982	16	2	31.6	23.1	76	17	185.63	4.760
Bangkok Metropolis*	455201	1982	17	2	31	24.2	80	15	178.09	2.465

Bangkok Metropolis*	455201	1982	18	2	31.5	24.6	78	18	180.72	3.910

Sample output data from CCAM.

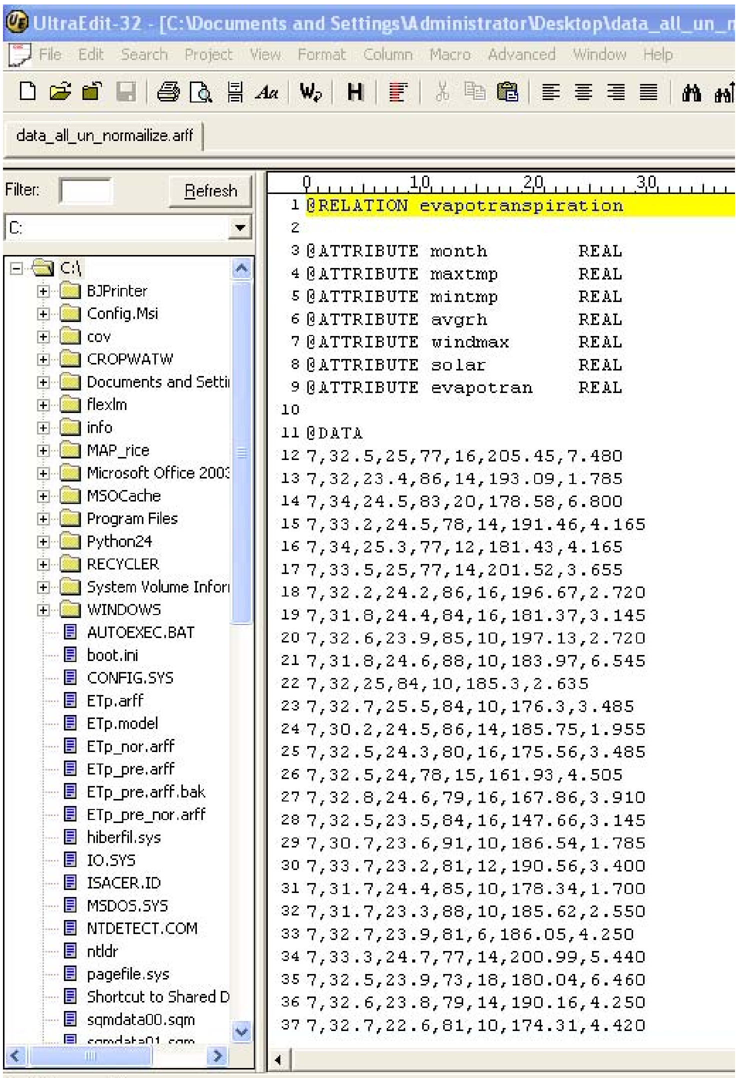


APPENDIX B
WEKA

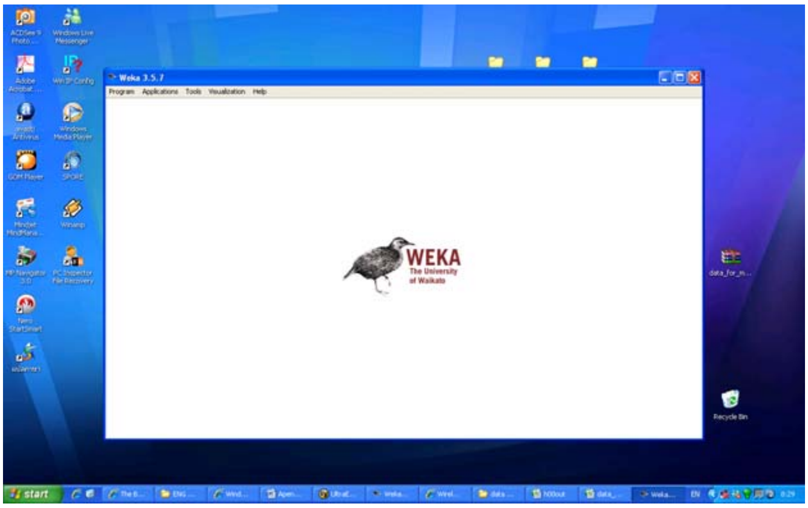
Sample Building ANNs model by WEKA.

ARFF format data from actual data for input WEKA.

- Select data to input WEKA.
- Convert data to ARFF format.

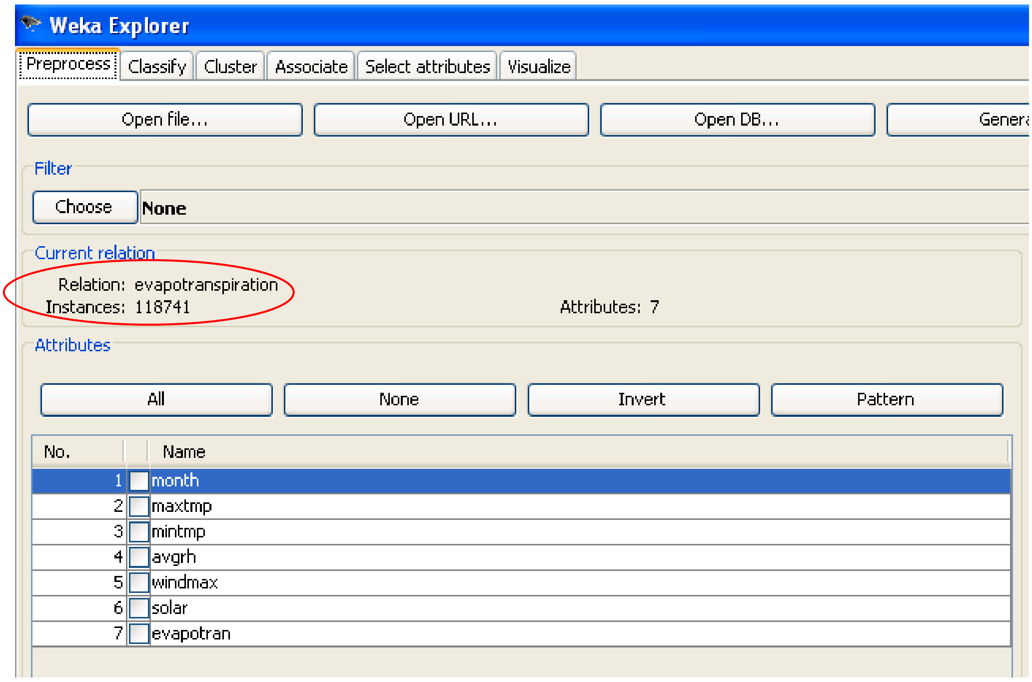


The first page is starting WEKA.

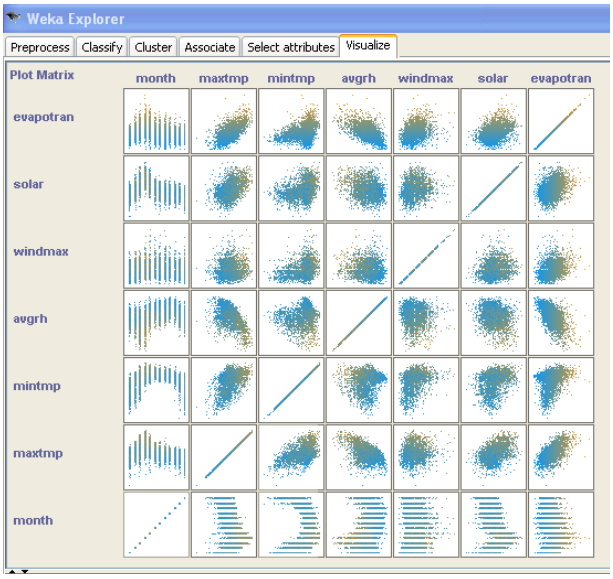


Input data to WEKA.

- Start program WEKA
- Click open file
- Select ARFF file

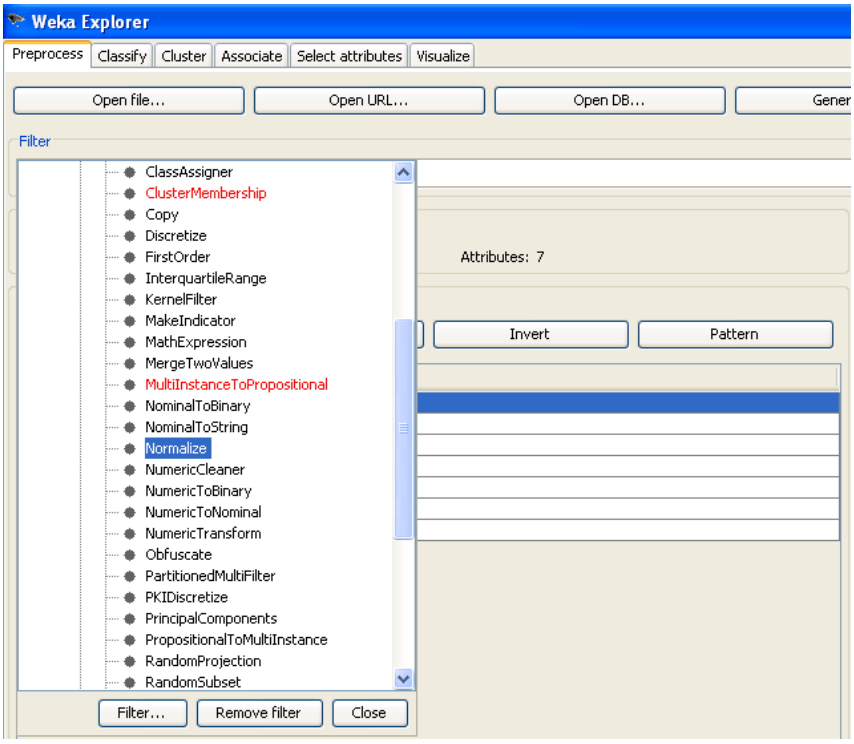


Matrix graph show correlation variables.



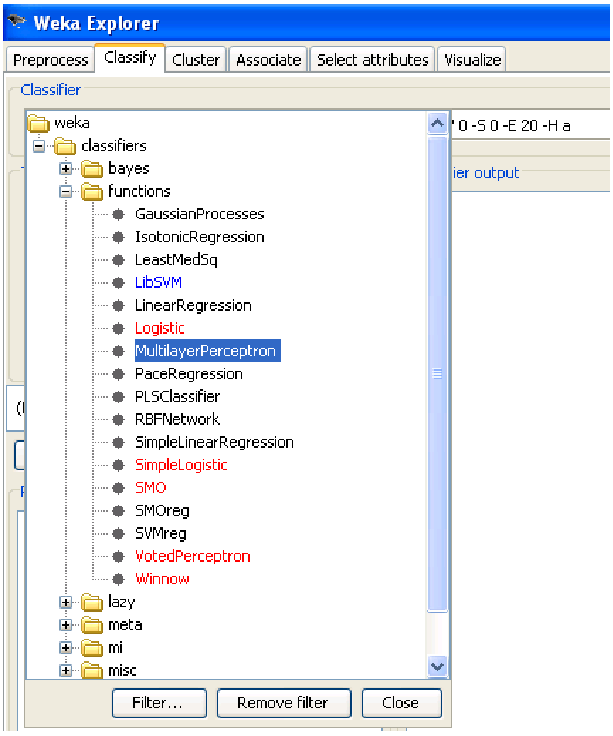
Calculate data using normalize function before build ANNs model.

- Click button choose
- Select normalize function
- Click apply



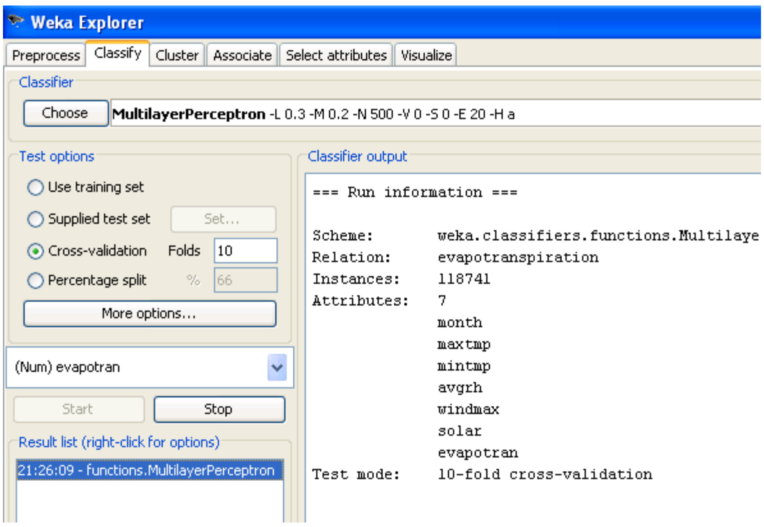
Build ANNs model.

- Click classify
- Choose MultilayerPerceptron (ANNs)



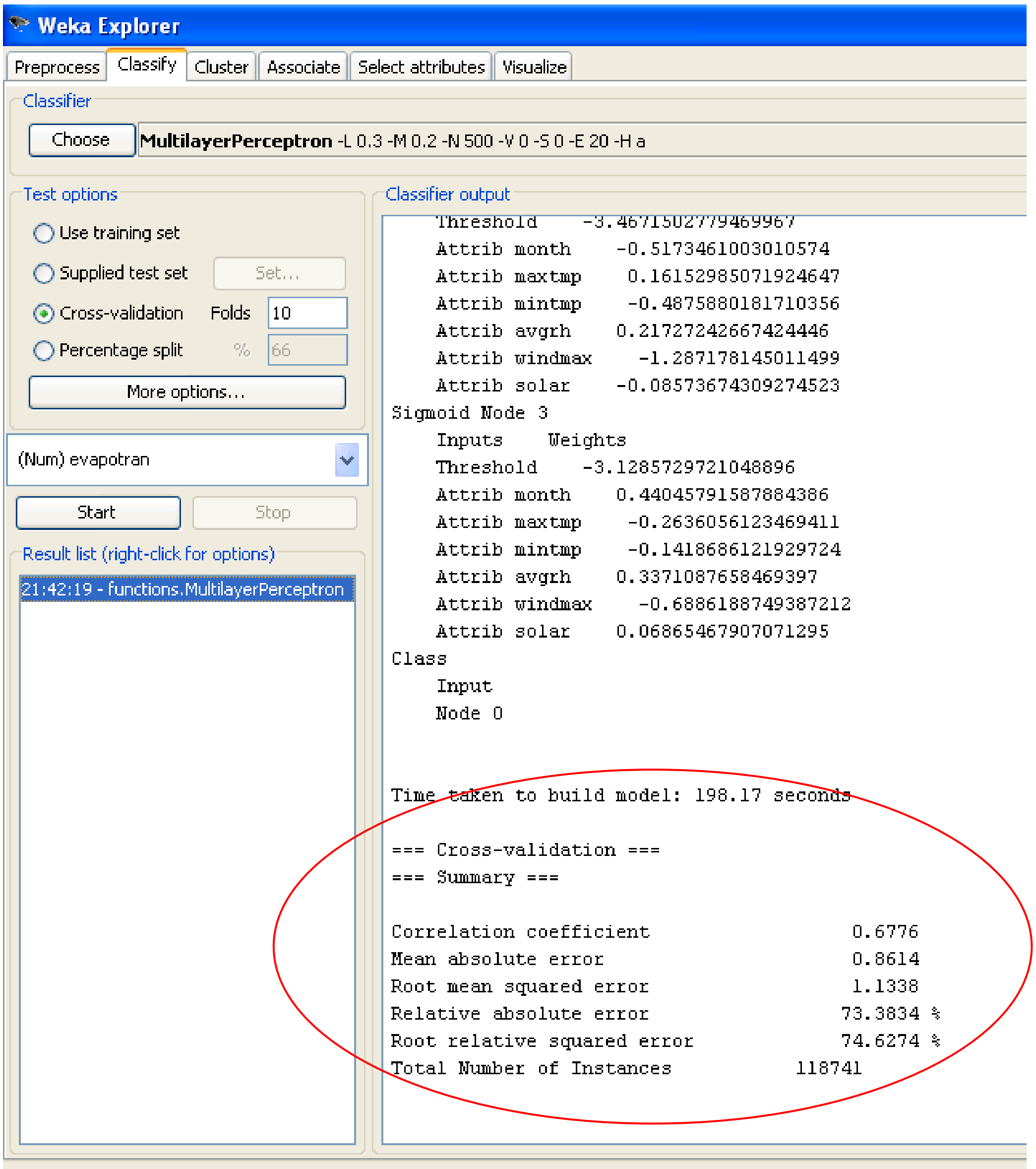
Start training ANNs model.

- Choose architecture
- Click start for run model



Result trained ANNs model and use the best result for predict ETo.

- It has to continue run sensitivity model for optimum RMSE.
- When model optimum RMSE was completed, using model for predict ETo.



APPENDIX C
OUTPUT DATA

Actual ET_o data average monthly in 1980-1989.

STATION	LAT	LONG	1	2	3	4	5	6	7	8	9	10	11	12
ARANYAPRATHET	13.75	102.55	4.06	4.36	5.26	5.32	4.69	4.19	4.07	4.11	3.79	3.47	3.59	3.63
BANGKOK METROPOLIS	13.75	100.55	4.08	4.56	5.29	5.69	5.21	4.55	4.53	4.59	4.00	3.56	3.62	3.94
BHUMIBOL DAM	17.25	99.05	3.19	4.51	5.57	5.86	4.98	3.75	4.16	3.82	3.53	2.97	2.72	2.75
CHAIYAPHUM	15.85	102.05	4.44	4.93	6.05	6.36	5.24	4.58	4.81	4.10	4.01	3.95	4.37	4.20
CHANTHABURI	12.65	102.15	4.05	3.84	4.17	4.08	3.72	3.20	3.25	3.13	2.88	3.16	3.81	4.21
CHIANG MAI	18.75	98.95	2.99	4.04	4.91	5.74	5.34	4.13	3.74	3.65	3.84	3.54	2.96	2.30
CHIANG RAI	19.95	99.85	2.56	3.78	4.93	4.89	3.76	2.86	2.33	2.23	2.18	2.12	1.90	1.94
CHON BURI	13.35	101.05	3.76	3.83	4.61	4.72	4.18	4.32	4.22	4.06	3.68	3.30	3.48	3.87
E	15.25	105.55	2.18	4.26	5.24	6.44	5.41	2.54	2.08	1.96	1.92	2.31	3.33	3.38
HUA HIN	12.55	99.85	3.67	4.42	4.89	4.90	4.44	4.10	4.03	3.90	3.45	3.47	3.40	3.74
KAMPHANG PHET	16.85	99.85	3.18	3.80	4.51	4.89	3.99	3.55	3.51	3.33	3.15	2.75	2.64	2.82
KANCHANABURI	14.05	99.55	3.88	4.72	5.74	6.35	5.38	4.46	4.77	4.53	4.21	3.49	3.28	3.64
KHLONG YAI	12.05	102.75	4.01	4.08	4.31	4.31	3.87	2.84	2.78	2.63	2.97	2.98	3.41	3.98
KHON KAEN	16.45	102.85	3.64	4.22	5.26	5.72	4.77	4.46	4.39	3.80	3.51	3.46	3.60	3.55
LAMPANG	18.25	99.55	2.50	3.37	4.38	5.27	4.75	3.82	3.60	3.46	3.13	2.80	2.46	2.19
LAMPHUN	18.55	99.35	2.92	4.15	5.59	6.33	5.14	4.33	4.25	3.97	3.44	2.84	2.61	2.50
LOEI	17.45	101.75	2.89	3.63	4.41	4.82	4.04	3.70	3.64	3.18	3.06	2.97	2.80	2.69
LOP BURI	14.85	100.65	4.41	4.47	5.49	5.78	5.13	4.65	4.53	4.19	3.92	3.39	4.04	4.43
MAE HONG SON	19.35	97.85	2.72	3.60	4.95	6.07	5.55	3.86	3.47	3.27	3.49	3.40	2.71	2.36
MAE SARIANG	18.15	97.95	2.47	3.50	4.54	5.56	4.77	2.92	2.71	2.65	3.03	3.05	2.60	2.42
MAE SOT	16.05	99.55	3.44	4.66	5.82	6.23	4.68	2.84	2.76	2.68	2.96	3.41	3.36	3.27
MUKDAHAN	16.45	104.75	3.65	4.03	5.03	5.24	4.28	3.74	3.74	3.13	3.42	3.47	3.72	3.39
N	20.45	99.95	1.46	4.05	5.38	7.07	6.83	3.76	3.58	3.51	2.68	2.62	3.39	2.68
NAKHON PHANOM	17.45	104.75	3.19	3.46	4.05	4.57	3.90	3.28	3.40	2.96	3.16	3.18	3.38	3.08
NAKHON RATCHASIMA	14.95	102.05	3.71	4.12	5.01	5.31	4.71	4.43	4.75	4.14	3.65	3.29	3.52	3.56
NAKHON SAWAN	15.85	100.15	4.02	5.44	6.45	7.24	5.84	4.99	4.74	4.26	3.78	3.39	3.43	3.60
NAN	18.75	100.75	2.44	3.01	3.88	4.28	3.91	3.25	3.03	3.04	2.89	2.73	2.36	2.30

NONG KHAI	17.85	102.75	3.13	3.53	4.23	5.10	4.40	3.47	3.32	3.02	3.48	3.25	3.25	3.02
PATTAYA	12.95	100.95	4.08	4.22	5.20	5.14	4.77	4.90	4.71	4.86	3.80	3.40	3.83	3.93
PHAYAO	19.15	99.95	3.14	3.90	5.04	5.22	4.12	3.78	3.65	3.39	3.06	2.68	2.43	2.61
PHETCHABUN	16.45	101.15	3.40	3.97	4.86	5.41	4.37	3.61	3.28	3.14	3.15	3.35	3.33	3.30
PHETCHABURI	13.15	99.95	3.33	3.81	4.87	5.22	4.63	3.93	4.04	3.88	3.67	3.12	3.12	3.33
PHITSANULOK	16.75	100.25	3.34	4.16	5.01	5.65	5.30	4.55	4.18	3.86	3.68	3.54	3.30	3.08
PHRAE	18.15	100.15	3.42	4.31	5.79	5.96	5.30	4.47	4.07	4.06	3.82	3.49	3.07	3.06
PRACHIN BURI	14.05	101.35	3.86	3.78	4.61	4.74	4.12	3.90	4.00	3.85	3.82	3.51	3.66	3.81
PRACHUAP KHIRI KHAN	11.85	99.75	3.87	4.34	4.88	4.95	4.40	3.76	4.02	3.80	3.67	3.54	3.66	4.13
RAYONG	12.65	101.35	4.06	4.24	4.77	4.94	4.40	4.43	4.38	4.50	3.74	3.34	4.00	4.24
ROI ET	16.05	103.65	3.56	3.84	4.61	5.07	4.36	3.76	3.74	3.40	3.20	3.26	3.55	3.51
S	11.05	99.35	3.43	3.84	3.87	5.16	4.54	3.55	3.57	3.43	3.06	2.90	2.93	3.42
SAKON NAKHON	17.15	104.15	3.75	4.20	5.15	5.53	4.30	3.71	3.85	3.48	3.47	3.63	3.79	3.59
SUPHAN BURI	14.45	100.15	3.72	4.28	5.18	5.87	5.50	4.79	4.75	4.46	4.10	3.67	3.56	3.61
SURIN	14.85	103.55	4.32	4.55	5.34	5.55	4.51	4.19	4.13	3.78	3.64	3.36	3.76	3.87
TAK	15.85	99.15	3.69	5.37	7.33	7.48	5.70	4.36	4.65	4.03	3.96	3.00	2.73	2.94
UBON RATCHATHANI	15.25	104.85	4.40	4.74	5.66	5.72	5.12	4.22	4.27	3.87	3.54	3.56	4.11	4.16
UDON THANI	17.35	102.85	3.81	4.31	5.28	6.12	5.12	4.62	4.52	3.86	3.67	3.53	3.66	3.49
UTTARADIT	17.65	100.15	3.26	3.95	4.99	5.30	4.65	3.78	3.48	3.39	3.37	3.40	3.15	3.01
W	18.45	97.45	3.12	4.53	5.38	6.34	4.62	1.82	1.30	1.27	1.40	1.89	3.10	3.63

Prediction ET_o data average monthly on CO_2 concentration 360 ppm

STATION	LAT	LONG	1	2	3	4	5	6	7	8	9	10	11	12
ARANYAPRATHET	13.75	102.55	2.37	3.97	4.95	6.60	5.45	3.08	2.60	2.53	2.27	2.14	3.03	3.31
BANGKOK METROPOLIS	13.75	100.55	3.27	4.18	5.13	6.39	4.98	2.84	2.52	2.38	1.99	1.88	2.82	3.53
BHUMIBOL DAM	17.25	99.05	3.11	4.89	6.01	7.04	6.10	3.63	2.95	2.95	2.73	2.27	3.02	3.37
CHAIYAPHUM	15.85	102.05	2.53	4.58	5.87	7.54	6.31	3.51	2.87	2.59	2.21	2.20	3.76	3.40
CHANTHABURI	12.65	102.15	1.92	3.53	3.81	4.25	3.11	2.36	2.13	2.01	1.61	1.76	3.01	3.10
CHIANG MAI	18.75	98.95	3.13	4.48	5.43	6.70	6.26	3.57	3.08	3.04	2.49	2.06	2.80	3.50
CHIANG RAI	19.95	99.85	1.93	4.39	5.57	7.04	6.45	3.43	3.16	3.11	2.49	2.31	3.19	2.99
CHON BURI	13.35	101.05	1.92	3.56	4.62	5.75	4.32	2.71	2.65	2.41	1.88	1.68	2.50	3.16
E	15.25	105.55	2.18	4.26	5.24	6.44	5.41	2.54	2.08	1.96	1.92	2.31	3.33	3.38
HUA HIN	12.55	99.85	3.54	4.36	4.66	6.03	5.75	4.58	4.34	4.27	3.89	3.40	3.17	3.62
KAMPHANG PHET	16.85	99.85	1.85	4.56	5.57	6.81	5.29	2.42	1.76	1.58	1.61	1.79	3.04	3.48
KANCHANABURI	14.05	99.55	3.82	5.01	5.46	6.37	5.01	3.35	3.25	3.07	2.35	2.21	2.83	3.78
KHLONG YAI	12.05	102.75	2.45	4.19	4.52	4.31	3.48	2.71	2.08	1.89	1.92	2.86	3.85	3.19

KHON KAEN	16.45	102.85	2.58	4.33	5.60	7.95	6.45	3.49	2.86	2.75	2.22	2.15	3.74	3.34
LAMPANG	18.25	99.55	4.50	5.09	6.06	6.87	6.17	3.85	3.27	3.23	2.83	2.51	3.51	3.60
LAMPHUN	18.55	99.35	2.91	4.92	6.03	7.75	6.50	3.53	3.03	2.97	2.47	2.42	2.83	3.24
LOEI	17.45	101.75	3.37	4.45	5.76	8.37	6.86	4.54	4.40	4.29	3.21	2.47	3.70	3.40
LOP BURI	14.85	100.65	2.31	3.96	5.14	6.40	4.76	2.23	1.96	1.84	1.53	1.55	3.01	3.16
MAE HONG SON	19.35	97.85	2.43	4.17	5.10	6.14	5.10	2.49	1.78	1.71	1.76	1.89	2.98	3.54
MAE SARIANG	18.15	97.95	2.21	3.97	4.53	5.26	3.88	2.15	1.71	1.63	1.70	1.98	3.03	3.57
MAE SOT	16.05	99.55	3.50	4.92	5.66	6.98	5.62	3.37	3.04	2.84	2.29	2.00	2.90	3.65
MUKDAHAN	16.45	104.75	2.07	4.32	5.57	7.46	6.27	3.40	3.04	2.88	2.63	2.64	3.65	3.57
N	20.45	99.95	1.46	4.05	5.38	7.07	6.83	3.76	3.58	3.51	2.68	2.62	3.39	2.68
NAKHON PHANOM	17.45	104.75	1.97	4.04	5.51	7.66	5.99	2.30	1.86	1.70	1.62	2.33	3.65	3.29
NAKHON RATCHASIMA	14.95	102.05	3.46	5.28	6.08	7.22	6.35	4.79	4.34	4.12	3.47	2.96	3.46	3.63
NAKHON SAWAN	15.85	100.15	2.05	3.92	4.94	6.30	4.72	2.67	2.49	2.23	1.75	2.06	2.62	3.04
NAN	18.75	100.75	3.17	5.17	6.31	7.54	6.12	2.93	2.28	2.10	2.06	2.47	3.60	3.55
NONG KHAI	17.85	102.75	2.48	4.80	5.86	7.40	5.81	2.65	2.36	2.12	1.45	1.57	3.40	3.17
PATTAYA	12.95	100.95	2.29	3.45	4.30	5.77	5.59	3.82	3.39	3.48	3.51	3.42	3.64	3.43
PHAYAO	19.15	99.95	2.30	4.47	5.75	7.23	6.42	3.30	2.66	2.58	2.21	2.36	3.28	3.25
PHETCHABUN	16.45	101.15	3.03	4.88	5.99	6.99	5.74	2.94	2.32	2.21	1.82	1.75	3.32	3.32
PHETCHABURI	13.15	99.95	3.67	4.66	5.20	6.34	5.43	3.75	3.49	3.20	2.29	2.03	2.95	3.62
PHITSANULOK	16.75	100.25	1.61	4.21	5.50	6.69	5.50	2.85	2.00	1.85	1.82	2.23	3.50	3.33
PHRAE	18.15	100.15	1.11	4.51	6.25	7.47	5.93	2.46	1.54	1.36	1.27	1.84	3.62	2.90
PRACHIN BURI	14.05	101.35	2.92	4.12	5.05	6.18	4.50	1.78	1.60	1.48	1.26	1.52	3.14	3.48
PRACHUAP KHIRI KHAN	11.85	99.75	3.26	3.85	4.16	5.66	5.11	3.89	3.88	3.85	3.36	3.31	3.08	3.47
RAYONG	12.65	101.35	2.08	3.02	3.68	5.44	5.50	3.92	3.37	3.33	3.49	3.56	3.90	3.36
ROI ET	16.05	103.65	2.29	4.61	5.69	7.69	6.46	3.27	2.70	2.54	2.10	2.24	3.66	3.39
S	11.05	99.35	3.43	3.84	3.87	5.16	4.54	3.55	3.57	3.43	3.06	2.90	2.93	3.42
SAKON NAKHON	17.15	104.15	2.23	4.08	5.86	8.88	6.87	3.21	2.52	2.40	2.30	2.87	3.88	3.44
SUPHAN BURI	14.45	100.15	2.47	4.44	5.35	6.59	5.11	3.01	2.93	2.78	2.25	2.15	2.95	3.37
SURIN	14.85	103.55	2.45	4.35	5.35	6.79	6.03	3.76	3.38	3.12	2.79	2.62	3.53	3.39
TAK	15.85	99.15	4.27	5.02	6.05	6.69	5.69	3.84	3.40	3.22	3.22	3.07	3.52	3.44
UBON RATCHATHANI	15.25	104.85	2.28	4.38	5.39	6.92	5.96	2.99	2.51	2.27	1.99	2.19	3.49	3.50
UDON THANI	17.35	102.85	3.36	4.80	5.82	7.82	6.41	3.50	3.16	3.01	2.14	1.97	3.51	3.39
UTTARADIT	17.65	100.15	2.26	4.97	6.43	7.44	5.63	2.42	1.73	1.57	1.39	1.70	3.32	3.17
W	18.45	97.45	3.12	4.53	5.38	6.34	4.62	1.82	1.30	1.27	1.40	1.89	3.10	3.63

Prediction ET_o data average monthly on CO_2 concentration 540 ppm

STATION	LAT	LONG	1	2	3	4	5	6	7	8	9	10	11	12
ARANYAPRATHET	13.75	102.55	2.05	3.92	5.35	6.45	4.97	3.03	2.70	2.63	2.18	2.24	3.10	2.76
BANGKOK METROPOLIS	13.75	100.55	2.85	4.28	5.41	6.51	4.52	2.88	2.63	2.31	2.01	1.95	3.13	3.18
BHUMIBOL DAM	17.25	99.05	3.26	4.88	5.95	6.82	5.70	3.56	3.11	3.10	2.61	2.19	2.76	3.35
CHAIYAPHUM	15.85	102.05	1.83	4.44	5.99	7.41	5.72	3.51	2.73	2.71	2.17	2.30	3.47	2.98
CHANTHABURI	12.65	102.15	1.69	3.54	4.00	3.78	3.04	2.50	2.12	1.91	1.53	1.93	3.08	2.84
CHIANG MAI	18.75	98.95	3.48	4.49	5.36	6.76	5.87	3.47	3.10	3.11	2.32	1.98	2.55	3.37
CHIANG RAI	19.95	99.85	2.25	4.41	5.53	6.85	5.88	3.26	3.07	3.05	2.27	2.20	2.78	2.99
CHON BURI	13.35	101.05	1.56	3.68	4.82	5.69	3.97	2.86	2.59	2.38	1.93	1.77	2.75	2.76
E	15.25	105.55	2.10	4.26	5.14	6.52	4.63	2.45	2.15	2.16	2.03	2.47	3.20	2.99
HUA HIN	12.55	99.85	3.24	4.32	4.92	6.12	5.79	4.79	4.36	4.33	3.87	3.43	3.31	3.49
KAMPHANG PHET	16.85	99.85	0.68	4.19	5.41	6.74	4.70	2.32	1.83	1.79	1.59	1.91	2.86	3.05
KANCHANABURI	14.05	99.55	3.58	5.09	5.75	6.42	4.80	3.67	3.24	2.93	2.39	2.27	2.99	3.48
KHLONG YAI	12.05	102.75	2.30	4.37	4.61	4.04	3.54	2.79	2.34	2.30	2.13	3.20	3.81	3.09
KHON KAEN	16.45	102.85	1.91	4.02	5.60	7.46	5.82	3.46	2.64	2.78	2.12	2.30	3.35	3.11
LAMPANG	18.25	99.55	4.97	5.19	6.05	6.87	5.80	3.73	3.32	3.32	2.67	2.31	3.14	3.89
LAMPHUN	18.55	99.35	2.99	4.82	6.00	7.65	6.04	3.49	3.09	3.09	2.35	2.32	2.59	3.25
LOEI	17.45	101.75	3.63	4.59	5.75	7.36	6.10	4.50	4.22	4.29	3.00	2.36	3.13	3.26
LOP BURI	14.85	100.65	1.86	3.94	5.30	6.36	4.10	2.28	1.99	1.96	1.51	1.71	2.97	2.74
MAE HONG SON	19.35	97.85	2.63	4.25	5.08	6.36	4.69	2.34	1.84	1.87	1.77	2.03	2.72	3.20
MAE SARIANG	18.15	97.95	2.36	4.12	4.63	5.36	3.22	2.01	1.72	1.79	1.73	2.23	3.07	3.14
MAE SOT	16.05	99.55	3.36	4.87	5.58	6.74	5.23	3.48	3.13	2.95	2.19	1.97	2.78	3.47
MUKDAHAN	16.45	104.75	1.78	4.01	5.70	7.28	5.43	3.35	3.04	3.03	2.58	2.91	3.45	3.15
N	20.45	99.95	1.60	4.11	5.43	6.81	6.40	3.53	3.39	3.45	2.55	2.49	2.88	2.68
NAKHON PHANOM	17.45	104.75	1.33	3.83	5.48	7.20	4.84	2.10	1.84	1.85	1.76	2.65	3.37	2.81
NAKHON RATCHASIMA	14.95	102.05	3.25	5.06	6.24	7.28	6.04	4.92	4.45	4.39	3.51	2.94	3.21	3.38
NAKHON SAWAN	15.85	100.15	1.00	3.84	4.89	6.19	4.18	2.79	2.53	2.47	1.74	2.11	2.50	2.72
NAN	18.75	100.75	2.61	4.89	6.14	7.48	5.33	2.70	2.27	2.17	2.03	2.50	3.20	3.39
NONG KHAI	17.85	102.75	2.21	4.72	5.89	7.08	4.96	2.36	2.24	2.05	1.38	1.78	2.94	2.93
PATTAYA	12.95	100.95	2.09	3.49	4.34	5.64	5.50	4.13	3.71	3.62	3.60	3.45	3.66	3.06
PHAYAO	19.15	99.95	2.30	4.55	5.72	7.17	5.86	3.11	2.63	2.57	2.10	2.27	2.95	3.05
PHETCHABUN	16.45	101.15	2.55	4.88	5.81	6.90	4.94	2.95	2.41	2.40	1.84	1.84	2.94	2.93
PHETCHABURI	13.15	99.95	3.18	4.63	5.36	6.54	5.19	3.86	3.39	3.10	2.30	2.14	3.19	3.38

PHITSANULOK	16.75	100.25	0.88	4.16	5.44	6.73	4.84	2.66	2.10	2.08	1.84	2.46	3.25	2.83
PHRAE	18.15	100.15	-0.23	4.12	5.81	7.34	5.35	2.20	1.59	1.45	1.30	2.09	3.23	2.78
PRACHIN BURI	14.05	101.35	2.55	4.15	5.31	6.11	3.89	1.95	1.70	1.55	1.24	1.66	3.16	3.14
PRACHUAP KHIRI KHAN	11.85	99.75	2.99	3.77	4.50	5.71	5.19	3.99	3.78	3.74	3.40	3.32	3.21	3.45
RAYONG	12.65	101.35	1.53	3.03	3.67	5.13	5.39	4.20	3.68	3.67	3.72	3.64	3.80	3.03
ROI ET	16.05	103.65	1.58	4.36	5.80	7.47	5.64	3.20	2.62	2.66	2.09	2.45	3.41	3.12
S	11.05	99.35	3.21	3.76	4.18	5.33	4.80	3.84	3.62	3.39	3.03	2.96	3.20	3.38
SAKON NAKHON	17.15	104.15	1.75	3.90	5.70	8.42	5.70	2.97	2.27	2.36	2.24	2.89	3.52	3.17
SUPHAN BURI	14.45	100.15	1.95	4.41	5.55	6.52	4.63	3.17	2.89	2.81	2.23	2.21	3.03	2.91
SURIN	14.85	103.55	1.97	4.17	5.56	6.78	5.53	3.89	3.39	3.26	2.78	2.75	3.35	3.00
TAK	15.85	99.15	4.54	5.12	5.96	6.56	5.30	3.83	3.40	3.28	3.12	2.77	3.21	3.49
UBON RATCHATHANI	15.25	104.85	2.04	4.40	5.49	7.00	5.15	2.98	2.50	2.46	2.05	2.38	3.36	2.91
UDON THANI	17.35	102.85	2.94	4.65	5.84	7.35	5.61	3.39	2.97	3.07	2.12	2.11	3.06	3.17
UTTARADIT	17.65	100.15	1.34	4.66	6.14	7.36	5.10	2.25	1.74	1.64	1.36	1.84	2.96	2.89
W	18.45	97.45	3.38	4.74	5.26	6.34	3.84	1.64	1.39	1.41	1.42	2.01	2.99	3.49

Prediction ETo data average monthly on CO_2 concentration 720 ppm

STATION	LAT	LONG	1	2	3	4	5	6	7	8	9	10	11	12
ARANYAPRATHET	13.75	102.55	3.12	4.17	5.98	7.49	6.49	3.67	2.92	2.86	2.54	2.41	3.26	3.14
BANGKOK METROPOLIS	13.75	100.55	3.89	4.72	5.92	6.91	6.11	3.39	2.82	2.81	2.35	2.12	3.31	3.38
BHUMIBOL DAM	17.25	99.05	3.74	4.98	6.44	7.72	7.59	4.61	3.45	3.27	2.97	2.33	3.18	3.28
CHAIYAPHUM	15.85	102.05	3.35	4.90	6.68	8.52	7.07	4.27	2.98	2.67	2.32	2.35	3.63	3.17
CHANTHABURI	12.65	102.15	3.00	3.80	4.14	4.67	4.22	2.85	2.42	2.26	1.86	2.14	3.06	3.17
CHIANG MAI	18.75	98.95	3.81	4.46	5.72	7.26	7.07	4.45	3.28	3.08	2.59	2.24	3.07	3.49
CHIANG RAI	19.95	99.85	2.92	4.34	5.87	7.60	7.65	4.27	3.08	2.89	2.43	2.42	3.08	3.06
CHON BURI	13.35	101.05	2.67	3.97	5.31	6.46	5.44	2.98	2.65	2.66	2.19	1.95	2.93	3.07
E	15.25	105.55	3.01	4.32	5.63	7.40	5.73	2.99	2.23	2.09	2.03	2.32	3.30	3.15
HUA HIN	12.55	99.85	4.02	4.56	5.44	6.53	6.58	5.16	4.77	4.77	4.29	3.51	3.58	3.64
KAMPHANG PHET	16.85	99.85	2.46	4.46	5.86	7.15	6.14	3.21	2.07	1.84	1.74	1.98	3.28	3.40
KANCHANABURI	14.05	99.55	4.34	5.11	6.13	6.80	6.04	3.88	3.77	3.60	2.88	2.46	3.38	3.44
KHLONG YAI	12.05	102.75	3.62	4.51	4.79	4.51	4.57	3.92	2.96	2.76	2.72	3.59	4.05	3.79
KHON KAEN	16.45	102.85	2.98	4.70	6.40	9.28	7.72	4.41	3.05	2.80	2.32	2.17	3.42	3.12
LAMPANG	18.25	99.55	5.01	5.20	6.11	7.12	6.66	4.53	3.46	3.32	2.86	2.44	3.39	3.89
LAMPHUN	18.55	99.35	3.48	4.82	6.60	8.79	7.76	4.37	3.24	3.01	2.55	2.49	3.18	3.26
LOEI	17.45	101.75	4.11	4.72	6.52	9.68	8.56	5.41	4.47	4.22	3.33	2.41	3.31	3.36
LOP BURI	14.85	100.65	3.13	4.25	5.63	6.68	5.49	2.93	2.28	2.16	1.84	1.87	3.26	2.97

MAE HONG SON	19.35	97.85	3.03	4.27	5.19	6.43	5.62	3.06	1.93	1.82	1.78	2.39	3.19	3.32
MAE SARIANG	18.15	97.95	2.91	4.17	4.73	5.58	4.24	2.39	1.85	1.72	1.71	2.50	3.45	3.34
MAE SOT	16.05	99.55	4.12	5.01	6.27	7.50	6.70	4.43	3.84	3.28	2.64	2.08	3.32	3.59
MUKDAHAN	16.45	104.75	2.97	4.56	6.56	8.53	7.12	3.99	3.22	2.99	2.71	2.86	3.69	3.31
N	20.45	99.95	2.51	4.06	5.58	7.57	8.11	4.63	3.40	3.29	2.64	2.68	3.12	2.81
NAKHON PHANOM	17.45	104.75	2.65	4.41	6.34	8.82	7.24	2.83	1.98	1.73	1.66	2.65	3.68	3.01
NAKHON RATCHASIMA	14.95	102.05	4.18	5.36	6.83	8.03	7.21	5.50	4.87	4.61	3.91	3.04	3.49	3.43
NAKHON SAWAN	15.85	100.15	2.74	4.15	5.32	6.43	5.43	3.66	3.13	2.75	2.15	2.25	2.98	2.85
NAN	18.75	100.75	3.74	5.30	6.65	8.21	7.08	3.57	2.34	2.02	2.02	2.52	3.41	3.43
NONG KHAI	17.85	102.75	3.31	5.15	6.49	8.33	7.02	3.45	2.38	2.04	1.49	1.74	3.12	3.00
PATTAYA	12.95	100.95	3.18	4.03	4.90	6.80	6.94	4.90	4.08	4.06	4.12	3.77	3.97	3.33
PHAYAO	19.15	99.95	3.26	4.75	6.18	7.93	7.22	4.09	2.69	2.48	2.18	2.40	3.19	3.10
PHETCHABUN	16.45	101.15	3.83	5.19	6.19	7.48	6.22	3.71	2.70	2.54	2.08	1.84	3.26	2.95
PHETCHABURI	13.15	99.95	4.30	4.89	5.95	6.79	6.30	4.17	3.61	3.38	2.65	2.20	3.38	3.49
PHITSANULOK	16.75	100.25	2.63	4.54	5.90	6.97	6.02	3.49	2.36	2.11	1.92	2.52	3.56	3.08
PHRAE	18.15	100.15	1.97	4.61	6.61	8.04	6.81	3.28	1.73	1.47	1.26	2.18	3.45	3.02
PRACHIN BURI	14.05	101.35	3.73	4.50	5.63	6.93	5.46	2.42	1.86	1.78	1.55	1.83	3.35	3.34
PRACHUAP KHIRI KHAN	11.85	99.75	3.73	4.04	4.91	6.19	5.80	4.30	4.22	4.31	3.82	3.40	3.45	3.57
RAYONG	12.65	101.35	3.12	3.58	4.24	6.37	6.82	5.39	4.31	4.15	4.23	3.99	4.16	3.35
ROI ET	16.05	103.65	3.13	4.80	6.62	8.89	7.27	4.06	2.88	2.64	2.31	2.37	3.59	3.29
S	11.05	99.35	3.93	3.95	4.50	5.78	5.22	4.05	4.18	4.01	3.44	3.09	3.38	3.38
SAKON NAKHON	17.15	104.15	2.91	4.48	6.99	10.66	8.38	3.81	2.38	2.13	2.17	2.65	3.55	3.33
SUPHAN BURI	14.45	100.15	3.31	4.79	6.06	7.19	6.16	3.70	3.26	3.09	2.70	2.41	3.37	3.06
SURIN	14.85	103.55	3.21	4.66	6.21	7.74	6.66	4.59	3.73	3.50	3.14	2.77	3.49	3.21
TAK	15.85	99.15	4.59	5.11	6.25	7.02	6.15	4.44	3.83	3.57	3.48	2.86	3.50	3.71
UBON RATCHATHANI	15.25	104.85	2.95	4.58	6.12	7.92	6.47	3.58	2.65	2.46	2.15	2.29	3.51	3.23
UDON THANI	17.35	102.85	3.87	4.98	6.31	8.71	7.43	4.27	3.23	2.99	2.30	2.05	3.10	3.20
UTTARADIT	17.65	100.15	3.18	5.13	6.68	7.92	6.64	3.26	1.79	1.67	1.45	1.96	3.26	2.93
W	18.45	97.45	3.73	4.57	5.50	6.77	5.21	2.36	1.49	1.38	1.46	2.30	3.41	3.64

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