# An analysis of cloud distribution to rainfall occurrence for future forecast improvement affecting urban living

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Abstract

Meteorological Remote Sensing data contain a vast amount of weather information. It is a valuable source of information in weather forecasting and early prediction of different atmospheric disturbances. Cloud conditions play an important role in many types of research such as weather and climate-related which can be utilized from the weather satellite data. In this research, Multi-functional Transport Satellite (MTSAT) meteorological satellite images are used for automatic extraction of cloud-top temperature feature for estimation rainfall occurrence which can be useful for urban living. The weather, especially the rainfall occurrence, has been found to have a significant impact on some phenomena related to human behavior in urban living. The gray level co-occurrence matrix (GLCM) algorithm is applied for measuring of cloud texture. Euclidean distance analysis was used to compare the similarity condition among rainfall occurrences. The relationship between rainfall distribution and the associated cloud properties using satellite image are evaluated for future forecast improvement in this study. The precision experiment yields 87.5% which can imply that the analysis is significantly improving if there is a sufficient spatial and temporal distribution of data exists.

Keywords: Cloud-top temperature, Rainfall occurrence, Remote Sensed data

## 1. Introduction

Rainfall is the important climatic element especially in the tropics because it determines many agricultural and hydrological activities, which are dominant in the economies of the developing countries. Most of the rainfall data in the regional scale is derived from weather station or rain gauge which providing temporal resolution.

The quality of such data is highly dependent on the data collection in methods and analysis in different countries. However, it is required to collect more information if there is a limitation in the quality of spatial rain gauge distribution, many types of research have been undertaken. Interpolation technique has been widely used to buffer rain intensity from rain stations. On the other hand, the availability of satellite remote sensing can fill the gap of rain gauge distribution by providing a wider area, high spatial and temporal resolution, real-time data.

Weather satellites made for the observation and measurement of atmospheric phenomena such as rain, cloud, and wind. Several weather satellites such as the Geostationary Meteorological Satellites (GMSs), Multifunctional Transport Satellites (MTSAT) and The Tropical Rainfall Measuring Mission (TRMM) are widely used for various meteorology, climatology, and agriculture applications.

Cloud can be better identified in the infrared image. It can play a significant role in rainfall analysis using the cloud brightness temperature products (Deepak, 2011). Several types of research focus on cloud detection for rainfall estimation. Moreover, it has the advantage to provide cloud conditions retrieval which can cause rainfall, covering a large area with temporal information.

As several researcher report that the spatial variation of rainfall greatly varies. However, to indicate exact cloud condition, the particular location of satellite image which rain gage is located is not sufficient to estimate the rainfall condition precisely. Cloud formation should be considered from connecting or neighboring pixels in order to monitor cloud direction and movement which significant to rainfall scenarios. Many research studied in cloud detection algorithms for meteorology satellite image which can be divided into three main methods such as the algorithms based on cloud texture and statistical features, networks classifier applying to cloud detection methods, and multi-spectral satellites images are applied in cloud detection.

The advantage of precipitation analysis over a large area with a high frequency of satellite image acquisition can be implemented from several remote sensing techniques. Cloud texture analysis using GLCM can be used for rainfall occurrence relations by measuring the directional pixels to detect the rain cloud objects. GLCM is the feature extraction method which can segment from image histogram distribution in order to retrieve and classify the object significantly by calculating the different direction measuring in particular window size.

This research is to develop the automatic cloud classification technique for MTSAT meteorological satellite imagery for weather observation. GLCM technique is applied for cloud distribution, and find the relationship between the amount of observed rainfall and cloud properties.

## 2. Material and Research Methodology

The main objective of this paper is to analyze the relationship between rainfall intensity and the associated cloud properties (cloud top temperature and cloud cover area) in the southern part of Thailand. To achieve this goal, three main steps of the work procedure were planned and implemented:

(1) Development of the automatic cloud classification

(2) Examination of the rainfall and cloud cover distributing patterns

(3) Analysis of the relationship between rainfall intensity and cloud properties (cloud top temperature and cloud cover area) based on the chosen case studies. Figure 1 presents a diagram of the analysis mentioned above in detail.

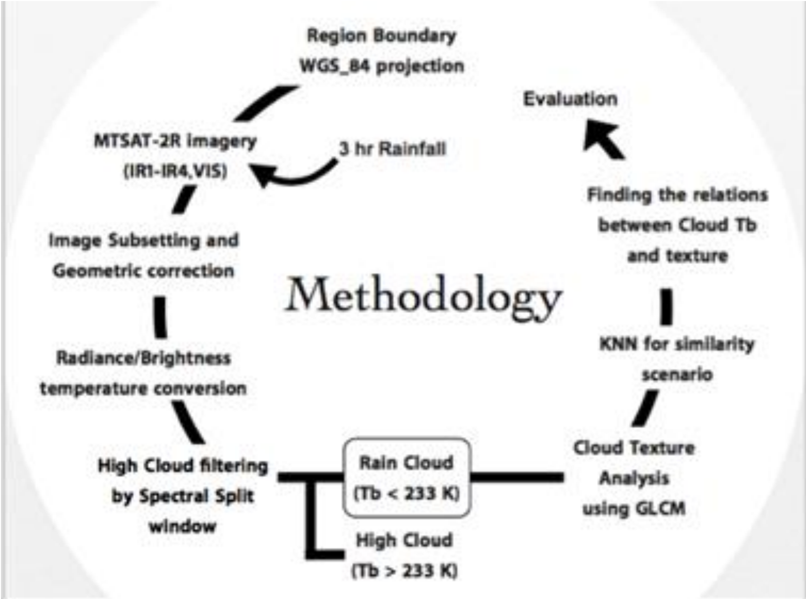


Figure 1: A diagram of the analysis.

Only heavy rain intensity will be considered for the analysis from the report of rain intensity classification from the Thai Meteorological Department. Rain stations of five provinces including Surathaini, Nakhon Si Thammarat, Phatthalung, Krabi, and Trang is in transition period to rainy season in Mar - May 2011. The dates that have rain intensity more than 90 mm/hr will be assumed as heavy rain dates.

2.1 Weather Satellites

The Multi-functional Transport Satellite (MTSAT) observes cloud and water-vapour distribution continuously during day and night as well as the land/sea surface and cloud-top temperatures. By analyzing these data, a range of useful information, such as the cloud top height, cloud distribution, cloud types (e.g., cumulus, stratus, cirrus, and cumulonimbus in the atmosphere can be obtained. The MTSAT-2R was used for this research. Table 1 summarizes the MTSAT instrument characteristics. The cloud cover for some selected dates, or periods, were also prepared based on raw data of MTSAT-2R satellite images in the visible and infrared regions, which can be downloaded from the website of the University of Tokyo in Japan api website (http://webgms.iis.u-tokyo.ac.jp/). Five bands of the VISSR sensor (1 visible and 4 TIR in Table 2.2) are available for the download. The spatial resolution of the visible image is about 1 km (nadir), and the TIR image is about 4 km (nadir).

Table 1: MTSAT instrument characteristics.

| Channel | Wavelength ($\mu$m) | Resolution (km) |
|---|---|---|
| VIS | 0.55-0.90 | 1 |
| IR1 | 10.3-11.3 | 4 |
| IR2 | 11.5-12.5 | 4 |
| IR3 (water vapor) | 6.5-7.0 | 4 |
| IR4 | 3.5-4.0 | 4 |

2.2 Cloud detection techniques

Widely algorithms have been developed to classify clouds and estimate the cloud-top height and optical thickness using split-window measurement with various thresholds. This paper applied the approach satellite image to classify cirrus clouds in the AVHRR images in which histograms of brightness temperature of the 11 $\mu$m channel and Tb difference (TbD) between split window data were constructed. The Tb of 253 K (-20°C) was defined as a cloud threshold of deep convection, and the TbD of 1 K was applied for the cirrus/cumulonimbus type cloud classification Inoue et al. (1987,1997,2004).

To classify the cloud types on the satellite images, the cloud-top temperature (CTT) is required. For MTSAT imagery, this CTT map was generated directly by using the standard look-up table for the radiance/Tb conversion provided for each image. The conversion table was formulated based on the Planck function and sensor's spectral response functions from which the approximated conversion formula is given in equation (1) (MSC, 2009):

$$B_i(T_b) = \frac{2hc^2 v_i^3}{\exp\left\{\frac{hcv_i}{k(a_{1i}+a_{2i}T_b)}\right\}-1} \qquad \text{(eq.1)}$$

Where,

Bi : sensor Planck function of channel i

Tb : brightness temperature

Vi : central wave number of channel i

a1i , a2i : band correction coefficients of channel i

h : Planck constant

k : Boltzmann constant c : speed of light

Values of the constants a1 and a2 for each band of MTSAT-2R are given in Table 2. In this context, the brightness temperature Tb is the equivalent temperature at the surface of the objects under the observation (along with the FOV line of sight) from which the measured radiance was first released. Values of the constants a1 and a2 for each band of MTSAT-2R are given in Table 2. In this context, the brightness temperature Tb is the equivalent temperature at the surface of the objects under the observation (along with the FOV line of sight) from which the measured radiance was first released.

The derived Tb map from objects that appear on the satellite image, only the cloud section of the image that was considered. The Tb threshold was applied at each of 20°C in the formulation of cloud cover image. This can make most off unnecessary objects such as non-rain cloud is filtered out from the map. The identification of cloud type on the image can refer that cloud pixel with a temperature less than -40 are likely to be rain-cloud like cumulonimbus; however, these can be cold high clouds like cirrus also. In this work, the brightness temperature data on used cloud images were classified into three classes (at the different interval of 20°C) as described in figure 2 (Vincenzo L. and Roberta A., 2002)

Table 2: Value of the constant a1 and a2 for each MTSAT-2R band [3].

| channel | Wavenumber | Band correction coef | |
|---|---|---|---|
| | $\nu$ (cm$^{-1}$) | ***a1*** | ***a2*** |
| IR1 (10.8 μm) | 926.4627 | 0.3597581 | 0.9987568 |
| IR2 (12.0 μm) | 835.6672 | 0.2195110 | 0.9991676 |
| IR3 (6.8 μm) | 1476.6898 | 0.3645235 | 0.9991492 |
| IR4 (3.8 μm) | 2684.1181 | 2.4635230 | 0.9967825 |

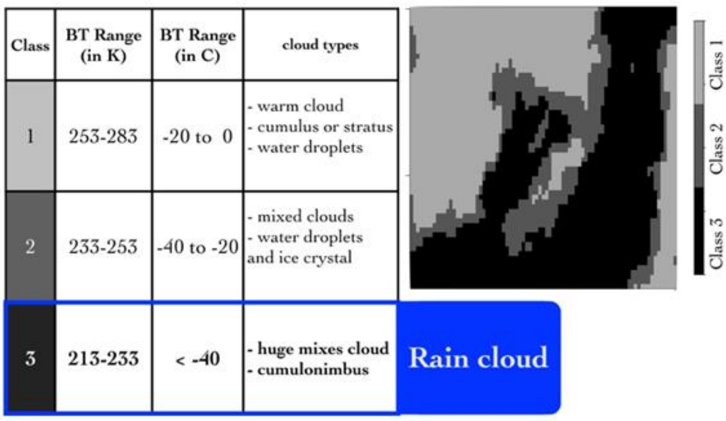


Figure 2: The classification scheme of cloud-top temperature map Examples of the classified CTT maps, class1: warm cloud, class 2: water droplet and class3: cumulonimbus cloud.

2.3 Cloud texture analysis

Due to significance and simplicity, the statistical approach GLCM is applied for satellite cloud image texture extraction. Gray Level Co-occurrence Matrix (GLCM) is a statistical method of examining texture that considers the spatial relationship of pixels in an image. This method characterizes the significant texture of an image by measuring the presence of the specific pairs and spatial relationship of the cloud object in an image including Energy, Homogeneity, Contrast, and Correlation [9]. The method to extract the cloud texture feature vectors is shown in figure 3.

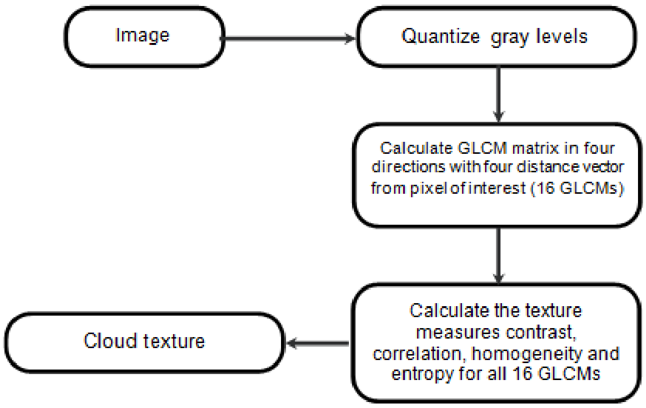


Figure 3: Extraction of the cloud texture feature vectors.

In this research using the 4-distance vector, in four directions the GLCM is created for cloud object measuring. The cloud texture measures contrast, entropy, correlation and homogeneity for totally 16 GLCMs which are calculated by the GLCM formula presented in table 3. The average value is calculated for the texture measures all GLCM variables. These average results are used as the texture feature vector.

Table 3: Descriptors used in Gray Level Co-occurrence Matrix.

| Type of GLCM | Descriptions | Equation |
|---|---|---|
| Contrast | Measure the local variations in the gray-level co-occurrence matrix. | $\sum_{i,j} \lvert i-j \rvert^2 \, p(i,j)^2$ |
| Homogeneity | Measure the closeness of the distribution of elements in the GLCM to the GLCM diagonal. | $\sum_{i,j} \frac{p(i,j)}{1+\lvert i-j \rvert}$ |
| Entropy | The entropy is a measure of randomness of grey level differences. | $\sum_{i,j} \lvert i-j \rvert^2 \, p(i,j)^2$ |
| Correlation | A measure of how a pixel is correlated to its neighbor over the entire image. | $\sum_{i,j} \frac{p(i,j)}{1+\lvert i-j \rvert}$ |

2.4 Texture similarity computation

The similarity between different cloud image feature vectors is computed using the Euclidean distance formula. Euclidean distance formula for comparing the similarities between different cloud images was used. The similarity between the gray levels feature vector of the initial cloud image, and the gray levels feature vectors of the compared image were calculated by the formula mentioned in the equation (2).

$$\text{Distance} = \sqrt{(\text{GLCM}(t)\text{-GLCM}(t+1))^2} \qquad \text{(eq.2)}$$

Where t: initial cloud image

2.5 System performance and evaluation

The most standard unite of measuring the performance of cloud classification is precision. This method is used to evaluate the performance of the system for the cloud image retrieval. In this research, the performance of the system is evaluated on the basis precision from the retrieving the images. Precision is defined as the ratio of the number of the relevant images to the total number of the images. It is a measure of the accuracy of the system and can be defined as equation (3) [10]:

$$\text{precision} = \frac{\text{No. of relevant images}}{\text{Total number of images}} \qquad \text{(eq.3)}$$

## 3. Results and Discussion

3.1 Cloud/rainfall leading Brightness temperature extraction

The intensity of rainfall amount depends directly on the type of cloud where heaviest rainfall is from a cumulonimbus cloud and light rain normally from the stratiform cloud. As these clouds naturally locate at a different altitude, therefore, their usual CTT tend to be distinguishable on satellite TIR images where cumulonimbus clouds have significantly lower CTT as their top surface situate much higher compared to the stratiform cloud, or other middle or low clouds. As a result, it is possible to identify the cumulonimbus cloud based on data of CTT and this knowledge can be related to the amount of the observed rainfall later on. Also, the amount of potential rain clouds as a whole (not only cumulonimbus) can be linked to rainfall observed each day which is also discussed in detail in this section.

The first research was conducted to examine general characteristics of the hourly CTT on the used MTSAT-2R satellite images and amount of maximum 3 hours rainfall observed in the region that was classified into four groups: 0-20, 20-35, 35-90, and more than 90 mm per hour. The classes represent days with light to very heavy rainfall respectively.

From figure 4, it can be concluded that sign of the rain cloud appearance (e.g., clouds with a temperature less than 233 K) are quite significant with rainfall intensity. Also, for heavier rain day, the fewer CCT values were normally found (where the CTT as low as 192 K could be found). The relationship between cloud/rainfall was investigated based on data of minimum CTT in the specified period and total rainfall amount observed during that period from some weather stations. The assumption is that the lower the CTT, the higher amount of rainfall observed.

Amount of rain rate is known to be related to the CTT of the rain clouds where the lower CTT indicate the higher amount of rainfall created. However, based on several previous studies, the pattern of this relationship is still depend to the period and places of the research. Most studies focused mainly on the cloud/rainfall relationship based on data at selected stations. Therefore, their results still cannot explain the variety of the cloud/rainfall relationship. To gain more knowledge of this cloud/rainfall distribution, covering wider area rain/cloud record using cloud texture-based classification is needed, which is significantly fulfilled in this research.

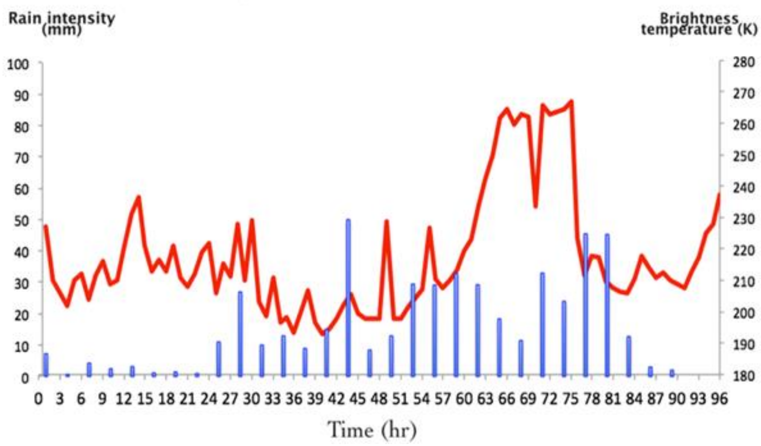


Figure 4: Comparison between rainfall amounts and the lowest CTT in 96 hours.

3.2 Texture feature extraction

The gray levels feature vector is represented by the frequencies of pixels that occur in each of the quantized bins. The texture feature vector is computed by taking an average of all the values of texture descriptors contrast, correlation, homogeneity, and energy, computed from the 16 GLCMs. The example of the average texture feature vector of the infrared satellite image is presented in Table 7.

Table 7: Average of the Texture feature vector.

| | Contrast | Correlation | Homogeneity | energy |
|---|---|---|---|---|
| Average value | 2.55639 | 1.04469 | 0.61388 | 3.725275 |

As a result of 4 texture feature vectors, GLCM values (contrast, correlation, homogeneity, entropy) of each image have similarity trend as show example MTSAT image on 24 March 2016 (00:32 UTC time). These values will be averaged to be a particular value for further similarity computation.

3.3 Similarity computation

The similarity between the different image is computed by the Euclidean distance formula. The similarity values of the image are evaluated with another image to compare the distance between each other. The reason for similarity value is to match cloud texture characteristic with other images which can be identified cloud motion based on time variable. As a result of similarity computation, pair images which have nearest values will be assumed as the same cloud/rain scenario. For example, at 00:32 and 06:32 hour of images in UTC time is the nearest images from similarity computation. Also, it has 11.2 and 10.06 mm/hr of rain intensity. These particular results can be determined that both images are a high possibility to have the same of cloud/rain distribution pattern.

The similarity value of one image is matched with another similar image as same cloud scenario. Then, matching image is compared with the measure rain rate from TMD observation in local time. If the matching image and the rain rate have the same rain scenario, it is assumed that cloud classification using cloud brightness temperature and texture analysis is precise. The main components of the cloud image analysis system are the cloud brightness temperature and cloud feature extraction. There are many features in the remote sensing image; feature selection is important to relate with rainfall information. The texture is an important feature in the cloud image. Different atmospheric conditions as rain and non-rain can be extracted by the feature pattern, and the gray level feature can differentiate between different types of clouds.

The performance of the system is evaluated by the precision in retrieving the images. Different numbers of images are all interesting period, and the precision is calculated from the formula mentioned in equation (3). The precision is evaluated based on the relevant scenario to all scenario: this research, the amount of cloud scenario which including IR1, IR2, IR3, IR4, and VIS channel are 2300 scenarios. As a result, the cloud classification algorithm provided relevant image scenarios about the 2012 scenario. Thus, the precision of cloud classification algorithm in this research is 87.5 percent. The precision is quite high in case of retrieving the images by the two features gray level, texture from cloud brightness temperature and cloud pattern.

Table 6: Example of similarity value between the first cloud image and the rest images.

| Image(hours) | Similarity value | Image(hours) | Similarity value | Image(hours ) | Similarity value |
|---|---|---|---|---|---|
| 1 | 0.000000 | 9 | 1439.089390 | 17 | 7141.580575 |
| 2 | 1360.364368 | 10 | 1441.178401 | 18 | 1405.497849 |
| 3 | 6911.147043 | 11 | 1442.781092 | 19 | 1439.133895 |
| 4 | 5515.281502 | 12 | 1442.671812 | 20 | 7154.717452 |
| 5 | 1437.953673 | 13 | 1443.117009 | 21 | 1441.644547 |
| 6 | 1442.224811 | 14 | 1402.967636 | 22 | 1441.736514 |
| 7 | 1440.489052 | 15 | 5.766435 | 23 | 1442.225960 |
| 8 | 1440.401065 | 16 | 1443.613611 | 24 | 8589.913291 |

## 4. Conclusion

Developing cloud classification algorithms, and cloud rain was the focus of this research for the future rainfall forecast improvement affecting the urban living. An automatic, simple cloud classification algorithm has been presented in the identification of cloudy pixels for the retrieval of cloud-related parameters (e.g., cloud heights) especially for clouds, which contribute to rainfall. Based on the cloud type algorithm developed and comparison with the observed rain gauge data, the conclusions are that satellite rainfall estimation using thermal infrared data depends on derived relations between satellite-observed clouds and rainfall. High clouds were filtered off at the beginning of the classifying process using a split-window technique which the threshold temperatures T11 (IR1) < 233 K (- 40$^{\circ}$C). However, derived relationship from one specific location is not related to another and low correlations between satellite data and rain gauge observations were found.

From the analysis of cloud and rainfall distribution and knowledge of weather information, it can be concluded that patterns of cloud and rainfall distribution in southern, Thailand are the product of the combined effects among several factors. Most observed rain occurred in interchange to rainy season March - May 2011.

The GLCM method of texture-based image retrieval considers the spatial relationships of pixels. It allows computing the texture of an image by specifying the offsets and the distance vector; these offsets can be defined in different directions with different distances with the pixel of interest.

Calculating the similarity between the images is the Euclidean distance, which is used to find the similarity between the cloud images. The similarity between image texture is computed to provide the weight to cloud feature. After the assignment of the weights to the different cloud features, final similarity value is computed between the images.

The performance of the analysis is evaluated by the precision which was calculated as the ratio of the number of relevant images to the total number of images retrieved which results in 87.5%. As a result, it can be suggested that the implementation is suitable for short-time forecast and gathering with other sources such as social sensing data for better accuracy and reliable for the application which can be much more useful for the urban living, especially influencing people's choice of activities. For future research, it should be studied focusing on how the weather impacts on urban-living activity patterns in different areas.

## 5. Reference


[1] Chonmapat Torasa (2009). **Near-Real time rainfall estimation using APT data from NOAA satellites and meteorological data.** School of Remote Sensing Institute of Science Suranaree University of Technology.

[2] Digata Kumar Sarma, Mahen Konwar, and Sanjay Sharma (2006). "Characteristic of brightness temperature with respect to rain rate over ocean land and its implication on rain rate retrieval", (September 2006) Indian Journal of Radio and Space Physics 35(4): 259-269.

[3] Japan Meteorological Agency. (2009). **Monitoring the earth from the MTSAT [Online].** Available: http://mscweb.kishou.go.jp/index.htm

[4] Dioszeghy, M. and Fejes, E. (1995). "Cloud classification derived from Meteosat data involving the standard deviation fields of the brightness values", Advances in Space Research Vol. 16, Issue 10, 1995, pp 33-36.

[5] Massons, J., Domingo, D. and Grau, J. (1996). "Automatic Classification of VIS-IR Meteosat images", Journal of Computers & Geosciences. 22(10): 1137-1146.

[6] Inoue, T. (1985). "On the temperature and effective emissivity determination of semitransparent cirrus clouds by bispectral measurements in the 10 μm window region", Journal of Meteorology Society Japan. 63: 88-98.

[7] Hayasaka, T. (1996). "Recent studies on satellite remote sensing of clouds in Japan. Advances in Space Research", Vol. 18, Issue 7, 1996, pp 29-36.

[8] Cooper, S., Ecuyer, T.L. and Stephens, G. (2003). "The Impact of Explicit Cloud Boundary Information on Ice Cloud Microphysical Property Retrievals from Infrared Radiances", Journal of Geophysical Research, Vol. 108, No. D3, 4107, doi:10.1029/2002JD002611, 2003, 1-17.

[9] R. Gonzalez (2009). **Digital image processing.** Dorling Kindersley: Pearson Prentice Hall.

[10] R. Holowczak, F. Artigas, Soon Ae Chun, June-Suh Cho, and H. Stone (2002). "An experimental study on content-based image classification for satellite image databases", IEEE Transactions on Geoscience and Remote Sensing (Volume: 40, Issue: 6, Jun 2002), pp 1338-1347.

[11] Pornthip Bumrungklang (2008). **An analysis of seasonal thunderstorm cloud distribution and its relation to rainfall occurrence in Thailand using remotely-sensed data.** School of Remote Sensing Institute of Science Suranaree University of Technology.

[12] American Meteorology Society. (2009). **Glossary of Meteorology [On-line].** Available: http://amsglossary.allenpress.com/glossary

[13] National Aeronautics and Space Administration-Cloud and Radiation (2009). **The Earth's Climate System Constantly Adjusts [On-line].**
Available: http://earthobservatory.nasa.gov/Features/Clouds.

[14] Dioszeghy, M. and Fejes, E. (1995). "Cloud classification derived from Meteosat data involving the standard deviation fields of the brightness values", Advances in Space Research Vol. 16, Issue 10, 1995, pp 33-36.

[15] Tsonis, A.A. and Isaac, G.A. (1985). "On a new approach for instantaneous rain are delineation in the midlatitudes using GOES data", Journal of Applied Meteorology and Climatology, Vol. 24: Issue 11, pp 1208–1218.