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Hydro-Meteorological Modeling and GIS for Operational Flood Forecasting and Mapping

L. Billa, S. Mansor, A. R. Mahmud and A. Ghazali

Dept. of Civil Eng., Fac. of Eng. Univ. of Putra, Malaysia

Abstract

In this paper a modeling process is presented for operational flood forecasting and mapping that integrates remote sensing for expected rainfall estimation, hydrological model (MIKE 11) and GIS for flood modeling. Based on a 1D cloud model, a quantitative precipitation forecast (QPF) using NOAA AVHRR and GMS data is established by relating cloud top temperature (CTT) below 235°K and cloud top reflectance (CTR) above 28% at cloud heights above 12000m for tropical rainfall. Mesoscale rainfall is determined in the range of 3-12 mm/hr to develop a grid based rainfall intensity map. Langat River Basin (about 2012km^2) in Malaysia with the flood event of 2000 is used as a case study to test the model. Basin parameters were calibrated for rainfall runoff using the NAM model based on observed rainfall for the flood of 2000. Alternatively the modeled QPF rainfall estimate was also used for rainfall runoff. The results of both runoffs were used to generate comparable flood polygons for the flood event in GIS. Results show similarities in the runoff hydrographs for both rainfall inputs to the runoff model. In using AVHRR satellite data rainfall estimates can be obtained based on the QPF model in advance of the actual rainfall, the study thus provides the framework for an operational flood forecasting before the actual flood event.

Keywords: NOAA AVHRR, QPF, Rainfall runoff, GIS, Flood Modeling

Introduction

Flooding induced by storm events is a major concern in many regions of the world (Horritt and Bates, 2002; Lee and Lee, 2003; Hudson and Colditz, 2003). Malaysia is not an exception as it lies in the path of north east and south west monsoon that affects the region. The extreme weather in recent years has demonstrated the necessity for reliable flood models, as emergency managers and city planners begin to realize the importance of advance warning in severe storm situations. As globally averaged temperatures increase, the potential for severe to extreme weather events increases (Becker and Grunewald, 2003; WMO, 2003). Therefore, global warming has brought further urgency to the prediction of flood levels and damages.

Flood forecasting and modeling has greatly improved in recent years with the advent of geographic information systems (GIS), radar-based rainfall estimation using next generation radar (NEXRAD), high-resolution digital elevation models (DEMs) and distributed hydrologic models (Bedient et al., 2003). However issues that limit the accuracy of some flood forecasts include errors associated with the radar rainfall input

(Vieux and Bedient, 1998; Borga, 2002; Grassotti et al., 2003; Jayakrishnan et al., 2004), realism of model structure (Horritt and Bates, 2002), availability of distributed data to parameterize and validate the models (Bates, 2004), and scaling theory to relate point measurements to grid averaged quantities predicted by the models (Beven, 2002; Bates, 2004). In addition and perhaps most importantly, the time required to convert the NEXRAD rainfall time series to a flood inundation map is critical in practical applications, especially during the extreme storm events that demand a highly efficient and timely prediction capability.

Despite the overall progress in flood modeling research, flooding continues in many areas of the world, including Malaysia where severe yearly monsoon rains results in flash floods that strike quickly and in most cases without warning. According to Keizrul and Chong (2002), these extreme monsoon phenomena are the most destructive natural disaster afflicting Malaysia in terms of the cost, damage to property and the area extent. Flooding is usually observed before any warning can be issued and usually persons and property have been affected before the warning reaches them.

Accurate and timely early warning of monsoon floods and tropical storms are instrumental to the reduction of flood impacts. Forecasting these impending floods requires adequate meteorological inputs such as real-time distributed rainfall from quantitative precipitation forecasts (QPF). However, since quantitative estimates of local rainfall are mostly unavailable before the actual rain event, it seem most practical to derive expected precipitation from the now commonly available satellite data as input to flood forecast. The need therefore arises for the close coupling of meteorological forecasts to hydrological models to improve flood forecasts and early warning in Malaysia. The problem however is to try to make estimates of precipitation from satellite data before the actual rainfall event and in areas where there are no monitoring stations.

Generally, the approaches that emerge for estimating precipitating amounts include point measurements (Rain-gauge GTS data), precipitation radar (NEXRAD) and satellite-based (NOAA-AVHRR and GOES) estimation techniques. Areal averages derived from rain-gauge observations suffer from limitations due to sampling but also because gauges are usually distributed with a spatial bias toward populated areas and against areas with high elevation and/or slope (Xie and Arkin 1998). An alternative ground-based estimation method is the use of precipitation radar but this is not always feasible in terms of cost and the lack of infrastructures (Grimes 2003). The again, their success is limited by the indirect nature of the relationship of the observations to precipitation and the fact that they require calibration using guage data. According to Grimes (2003), an answer to these limitations is likely to come from satellite remote sensing whose potential for estimating rainfall has been evident since its early days: the data are inexpensive, provide complete area coverage and are available in real time.

Satellite remote sensing methods that are appropriate for operational precipitation estimation usually rely on empirical relationships of metrological satellite (NOAA-AVHRR, GOES, Meteosat and GMS) data thermal infra-red (TIR) and passive microwave imagery. For a review of TIR precipitation estimation techniques see (Grimes *et al.* 1999; Todd *et al.* 1995; Xie and Arkin 1997). A number of studies exist that discusses various TIR methods, most of which argue its effective application in the tropical regions. Based on the classification of Barrett and Martin (1981), cloud based rainfall estimation methods from meteorological satellite data are divided into four main categories, broadly including the cloud life history, bispectral, cloud-indexing, and cloud model-based techniques. Each method stresses a particular aspect of the sensing of cloud physical properties using satellite imagery. Details of these methods are given by Griffith *et al.* (1978), Levizzani *et al.* (1990) and Scofield and Naimeng, (1994).

The two methods of cloud based rainfall estimation that come to mind are the cloud indexing and cloud model-based techniques that are combined in the model presented in this paper. The cloud indexing assigns rainfall levels to each cloud type identified in the satellite imagery on the basis of a high correlation between radar-estimated precipitation and fraction of the area colder than 235 K in the IR. This model was initially developed for NOAA-AVHRR data and later adopted for Geostationary images. The scheme, named GOES Precipitation Index (GPI) (Arkin and Meisner, 1987), assigns these areas a constant rainrate of 3 mm/hr, which is appropriate for tropical precipitation over 2.5° × 2.5° areas. Raining days are identified from the occurrence of IR brightness temperature (T_B) below a threshold at given location. Details of this method are given by Arkin and Janowiak (1991), Ba and Nicholson (1998) and Todd *et al.* (1995, 1999).

The cloud model techniques introduce cloud physics into the retrieval process for a quantitative improvement, and provide better physical description of the rain formation processes. The technique also introduces a cumulus convection parameterization that relates fractional cloud cover to rain-rate. Another of the cloud model methods is the convective stratiform technique (CST) which is a 1D model which relates cloud top temperature to rain rate and rain area. Local minima in the IR T_B are sought and screened to eliminate thin, non-precipitating cirrus. Slope parameter S is calculated for each temperature minimum T_{min} and T_{6-1} is the average temperature of the six closest cloud pixels in the image, if the T_{min} is located at (i,j). Extensive discussions of these techniques have been presented in Reudenbach *et al.* (2001), Bendix, (1997, 2000) and Anagnostou *et al.,* (1999).

Generally, most of the studies focus on interpreting precipitation on the continental and global scale, emphasizing the need for similar studies over small to regional scale area applications in support of hydrological processes such as surface runoff and flood forecast. The aim of this study is therefore to estimate rainfall from satellite data with a modification and model combination of the cloud indexing and model based techniques, which from now will be referred in the paper as QPF model. Rainfall is to be estimated at a mesoscale level as input to the operational flood forecast before the actual flood event. The objectives of the study are:-

1. To develop the framework for operational flood forecasting by integrating remote sensing, hydrological modeling and GIS
2. To estimate mesoscale grid precipitation through a QPF process using real-time NOAA AVHRR and geostationary (GMS-5) data and assimilate estimates into a Hydrological modeling processing
3. To simulate and compare rainfall-runoff based on the QPF and observed data in a suitably calibrated MIKE 11 NAM model for the study area
4. To couple the runoff result to a GIS model of the basin for flood mapping

Methodology and Database

The study area is the Langat River Basin in Selangor Malaysia; it is 2010km in area and comprises five sub-catchments of Lui, Kajang, Dengkil Semenyih and lower Langat. Details of the basin can be found at http://gwater.jmg.gov.my/mis/arep/genfeat .htm. The operational flood forecasting framework (Figure1) shows a three stage methodology that integrates a QPF, hydrological and GIS modeling processes. The MIKE 11 River modeling system was used for hydrological modeling due to its versatility for hydrological process and the ability to integrate with GIS. MIKE 11 hydraulic and NAM runoff models have shown to provide accurate and useful results in numerous flood related studies (DHI, 2003; MIKE 11, 2003; Madsen, 2000; Havno, *et al.*1995; Singh, 1995). The methodology was tested for the rainfall and flood event of 27th September to 12th October 2000 in the Langat Basin area.

Quantitative precipitation forecasting using (NOAA AVHRR and GMS data)

Ideally synoptic data are used to provide information on rainfall runoff and basin responses to flood mostly with short lead time; however for a flood forecast and early warning to be really effective, a long lead time of forecast is necessary to provide enough time for contingencies. Many studies suggest that meteorological satellite data provides the answer to this problem through the processing of data in TIR to retrieve cloud information that may be useful in determining local rainfall and predicting flood disaster.

In the study, NOAA AVHRR and GMS data were process for T_B in the TIR to determine top of clouds temperature below the threshold of 235^o K that have a probability to precipitate. The T_B test for the day pass AVHRR data involved processing entire scene's channels to top of atmosphere (TOA) reflectance and temperature in radiance using the calibration coefficients provided in the NOAA KLM User Guide (NOAA, 2000). The calibrated radiance in the data channels 4 and 5 were converted to the scene T_B using formulas supplied in NOAA AVHRR data processing software user's guide (Andersson, 2002). The scene T_B was masked to the area of interest (AOI) Langat Basin as shown in Figure 2 based on the cloud model technique and established empirical estimates that cloud top temperature (CTT) below 235^o K in the tropics produces rainfall of 3mm/hr. The values of T_B in the mask are displayed in a color schemes ranging from 179^o K to 295^o K.

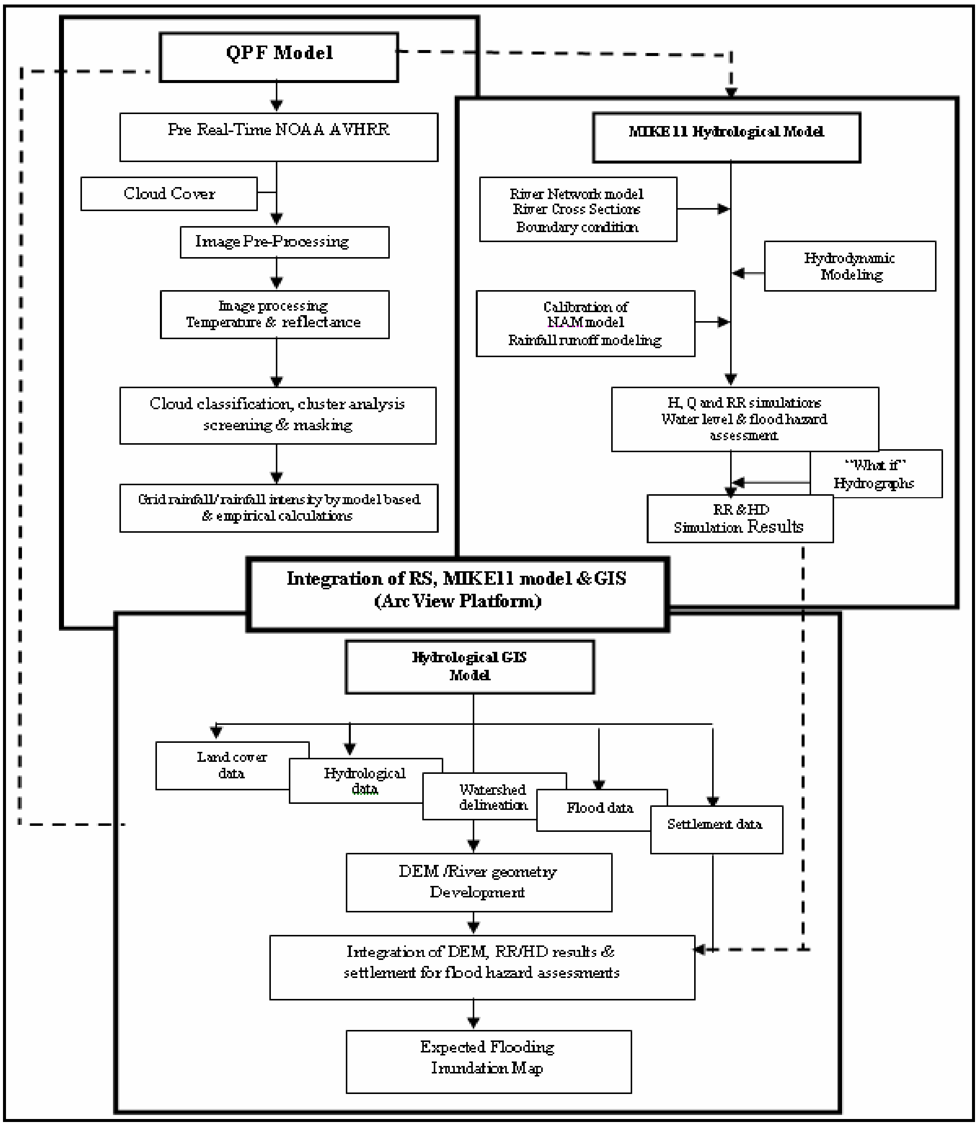

Figure 1: Framework of Operational Flood Forecasting

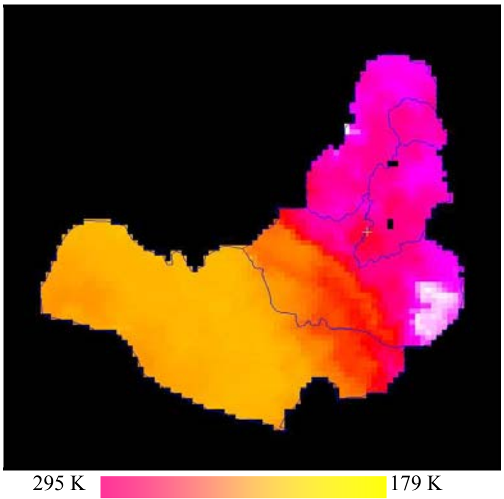

Figure 2: T_B in Degree Kelvin in AVHRR Masked to Langat Basin

The cloud pixels over the individual catchments show expected precipitating area in the Langat Basin for the T_B processed AVHRR scene. Further classification was performed using K-means to remove the fuzziness in cloud pixels and group pixels into mean clusters that shows mean average temperatures of cloud pixels classes. The K-means class clusters (Figure 3) represent the variation in rainfall intensity to which different rain-rates of 3 to 12 mm/hr were assigned. The estimation of the area rainfall or mean average rainfall for the portion of catchment covered by the cluster is computed based on the pixel count of the cloud fraction for the area and rainfall intensity.

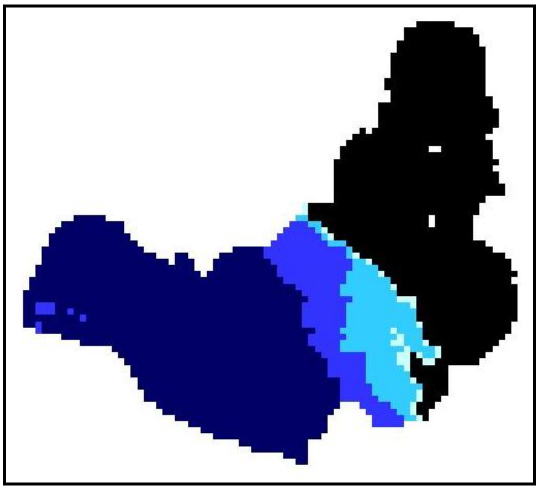

Figure 3: K-means Classification

Hydrological modeling for rainfall runoff process (MIKE 11 Model)

The rainfall input to the hydrological model was based the QPF and subsequently observed rainfall to facilitate comparison. The Langat hydrological model was implemented with the aim of analyzing the rainfall–runoff on an adequately calibrated MIKE 11 NAM model to best describe the basin characteristics. The hydrological modeling process forms the second methodological step of operational flood forecasting. It attempts to streamline rainfall input and floodplain output to enable the modeling of rainfall runoff relations with greater efficiency and also contribute to improvements in the ability of the model to respond to the scenarios of a disastrous flooding event in Malaysia.

Table 1: Assignment of rain-rate

T_B (^oK)	188-200	201 – 210	211- 225	226- 235	236
Assigned rain-rate (mm/hr)	12	8	6	3	0

Hydrological GIS for flood mapping (AcView GIS)

The hydrological GIS for the Langat river basin was developed with MIKE 11 GIS that has a flood management (FM) model with an associated DEM module for basin and flood plain surface development. A combination of point and contour elevation data were used to develop the surface DEM and together with other supporting data that include land cover, delineated catchment boundary and data on past flood to present the flood plain information. The result of the rainfall runoff simulation form the hydrological modeling process were imported and coupled to the DEM for the flood map generation. The flood extent was visualized and settlement data overlaid on the flood map to assess the damage due to the flood.

Results and Discussion

Precipitation which is a primary input to overland flow shows considerable spatial variation brought about by differences in the type and scale of development and is also strongly influenced by local or regional factors, such as topography and wind direction at the time of precipitation (Sumner 1988). In a large river basin however, heavy rainfall in the mountain upstream can result in severe flooding downstream thus the use of average distributed rainfall to determine runoff. As a foundation of the study to determine the level of average rainfall that may result in flooding, a careful study and comparison of monsoon rainfall rates, calibrated radar and temperature reading form complementary geostationary satellite data was carried out on periodic monsoon data covering 2003-2005. The comparison showed a high coefficient of determination with average $r^2 = 0.7617$ between rainfall rate and CTT. A steady rise in the correlation curve was observed at temperature of 220^o K where the rainfall level is about 5 mm. This relationship is in general agreement with the long established empirical observation of the relationship between rainfall and temperature in the tropical regions of the world. It also confirms the study of Vicente and Scofield (1998) whose similar work also established a high correlation between calibrated precipitation radar rain-rate and GOES–8 temperature readings. Based on the overall comparison Table 1 shows the rain rate established in relation to T_B in degree Kelvin.

Based on the QPF model, AVHRR data was processed for to establish a 1D T_B cloud model. As determine by the model, rain-rate of 3-12 mm/hr were assigned to each K-means cluster that has a direct relation on cloud top T_B. The model calculates maximum rain-rate as a function of maximum cloud height above 12000 m, maximum cloud top reflectance (CTR) above a threshold of 28% and minimum T_B below a threshold of 235 ^{o}K. The assumption is that every cloud pixel of the set thresholds has a beginning unit rain-rate of 3 mm/hr, considered from empirical studies to be the appropriate precipitation level over tropical areas within +/- 3^{o} around the equator (Anagnostou *at al.*, 1999).

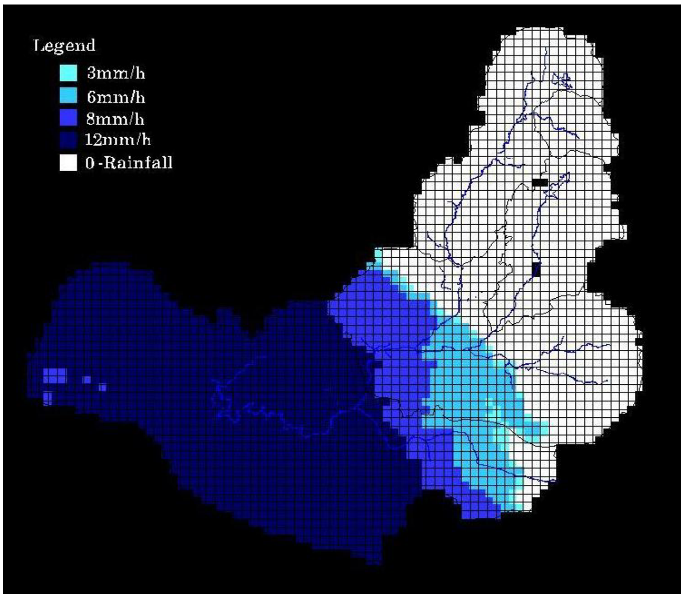

Figure 4: QPF Model Grid Based Rainfall

The entire basin rainfall is thus shown in Figure 4 from which rainfall coverage and volume can be estimated. The grid base rainfall area is assumed to have a pixel size of 1.1 km the same as the spatial resolution of the AVHRR data. The rain-area (A_r) is thus the total cold cloud fraction and the portion of the catchment or area covered by K-means class. By using a 1.1 km grid cell size**,** the area for each cell is calculated as 1.21 km^2. The pixel/cell count (P) for each K-means class as determined by the coverage of the classification, is used to estimate expected precipitation.

In the projected grid rainfall of the QPF (Figure 4) the assumed highest rain-rate area has pixel count P= 1055 based on the K-means class. Rainfall area estimate were computed as A_r = 1276.55 km^2 ,VR_r = 12660 mm, AV_r = 9.9 mm/hr:- using Equations

$$\mathrm{A_r} = \mathrm{P}\ (1.1^2\mathrm{T_c}) \qquad (1)$$

$$\mathrm{VR_r} = \mathrm{P}\ (R_r K_{\mathrm{means}}) \qquad (2)$$

The average rain rate over the raining area of K-means cell/pixel is

$$AV_r = VR_r / A_r \tag{3}$$

where:

P is the number of cells/pixels in K-means class,
VR_r is instantaneous volume rain-rate of K-means class
AV_r is the average rain rate of K-means
T_c is the K-mean temperate range below the threshold of 235 ^oK

In the hydrological modelling rain runoff was generated using hourly T_B readings from GMS-5 data for the QPF rainfall estimate and comparable observed rainfall tested on the flood event of 27th September to 8th October 2000 in the the Langat Basin. Figure 5 shows the comparison of runoff for the Kajang sub-catchment excluding the existing discharge. The coefficient of determination for the QPF runoff compared to the observed rainfall runoff for the event showed $r^2 = 0.9028$. The hydrological model was calibrated for the basin using observed discharge and evaporation and processed for the two rainfall series QPF and observed rainfall. The resulting calibrated runoff including observed discharge are presented in Figures 6 and 7 showing comparable hydrographs with r^2 of 0.926 and 0.819 for the observed and QPF rainfall respectively.

An exact agreement between the simulated and observed hydrographs was not achieved in both simulations although relatively high coefficients of determination were observed. The reasons for the disagreements were partly due to poor optimization of some the 9 calibration parameter input to the MIKE 11 NAM model. With an average RMSE of $R^2 = 0.873$ the calibration was considered suitable for the model application in the Langat Basin and possibly other basins with similar physical characteristics. The size of the basin and sub-catchments was not considered a constraint in the model application as studies (MIKE 11, 2003) has demonstrated the model can be employed in bigger catchments.

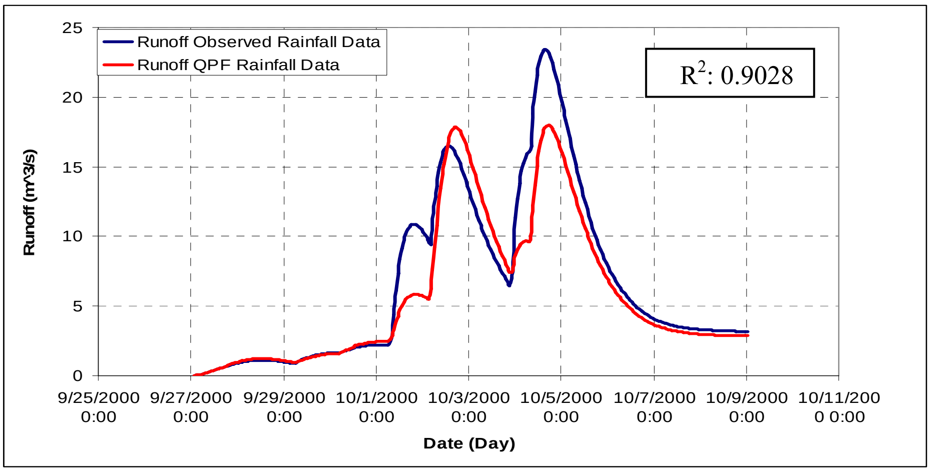

Figure 5: Comparison of Runoffs for Observed Rainfall and QPF Estimated for Kajang Sub-catchment

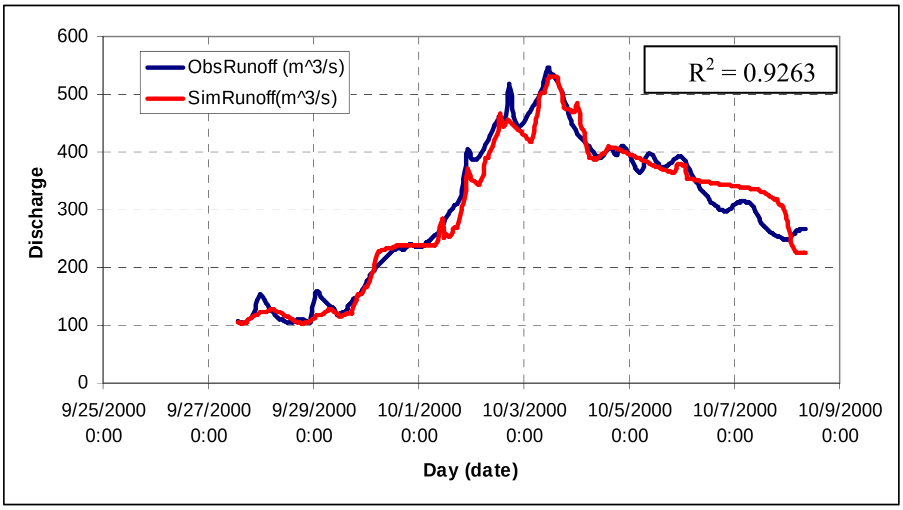

Figure 6: Observed Rainfall-Runoff (Kajang Sub-catchment)

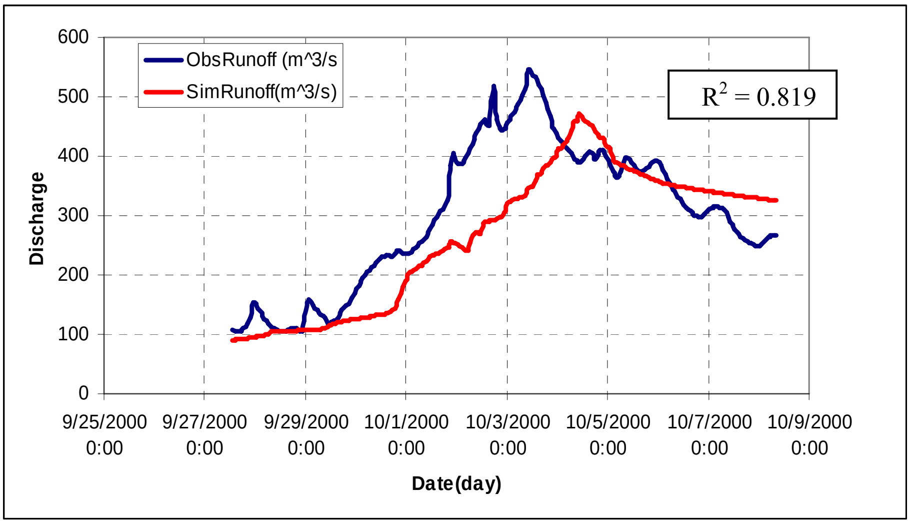

Figure 7: QPF Rainfall-Runoff (Kajang Sub-catchment)

The importance of a flood map as the basis of early flood warning cannot be over emphasized; maps constitute an effective media for representing the potential areas to be inundated. Its use as an early warning and emergency tool can only be effective if inundation maps are produced in advance of a flood event to provide ample time for contingence planning and also providing few false alarms. In the study, runoff simulation results in the hydrological modeling process were coupled to a GIS where the basin DEM and the river channel geometry were prepared. The resulting flood map is shown in Figure 8.

The flood depth (Figure 9) was generated and validated using 10 sampled flood depth point publish in the annual flood gazette (DID, 2000) for the Langat basin flood 2000. The map displays three depth classes ranging from 0-0.5, 0.6-1 and above 1 m. This range was determined by cross referencing the flood level shown in different colour tone in the flood map with measured flood level (river cross section depth subtracted from water surface height) at selected location in the coupled hydrodynamic and runoff simulation results. The validation of the flood depth based on the sampled points showed an accuracy of 70%, whilst measured depth in some places generally ranged between 1-2 m. The study is still ongoing and although encouraging results have been achieved, the validation of the flood extent is yet to be fully carried with the appropriate data.

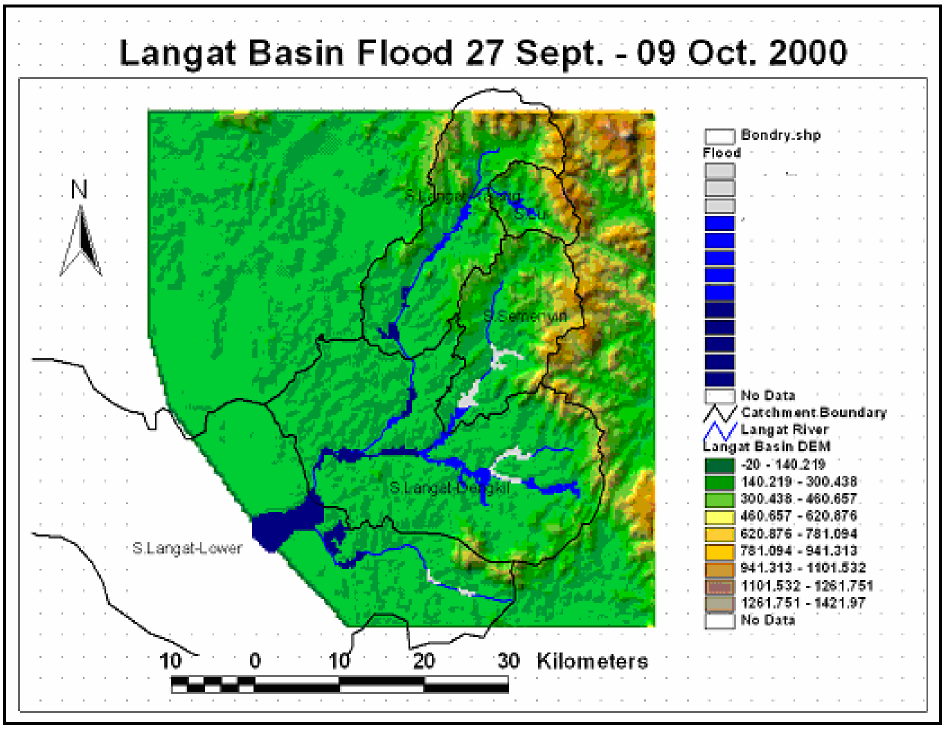

Figure 8: Flood Map

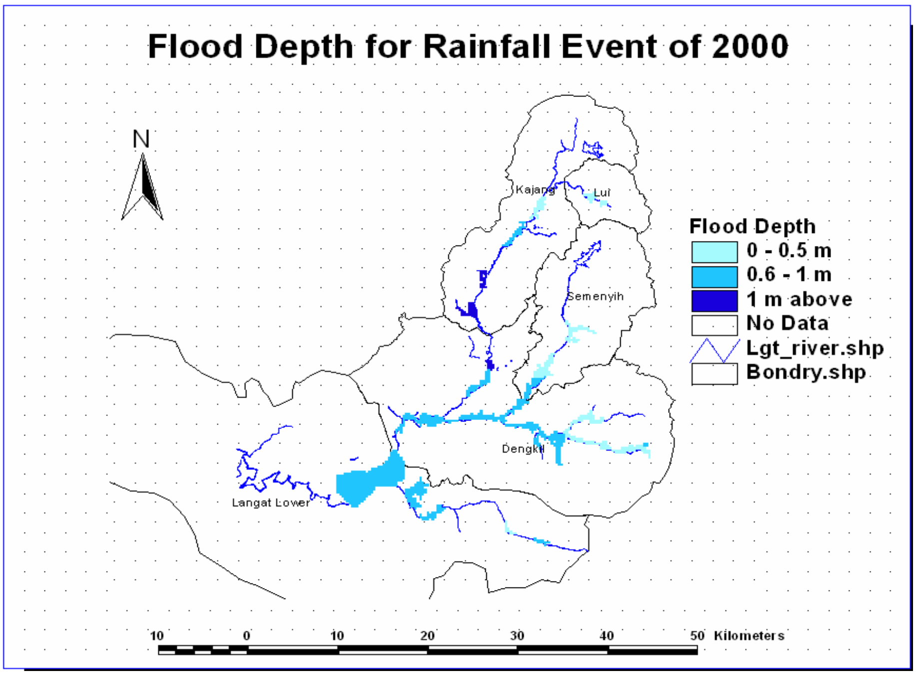

Figure 9: Flood Depth

Conclusion

A general framework of operational flood forecasting and early warning that integrated a three part methodological modeling process comprising QPF, hydrological simulation and hydrological GIS has been presented. A QPF process was introduce through the combination of cloud indexing and cloud model base technique to estimate rainfall from pre real-time AVHRR and GMS data. In the process a grid based rainfall map was produce to show the rainfall intensity for the Langat river basin. As a result area rainfall (A_r), instantaneous volume rain-rate (VR_r) and the average rain rate (AV_r) were estimated. Comparison of simulated runoffs for the QPF rainfall estimate and observed rainfall shows similarity with $r^2 = 0.9028$. Simulation result was again coupled to the DEM of basin to generate a flood map for the event of 2000, where the validation of flood depth achieved 70% accuracy. The study is ongoing and efforts are being made to acquire synthetic aperture radar (SAR) data to validate the flood extent.

Outside of the QPF modeling process and the assimilation of computed rainfall estimates to the hydrological modeling, the hydrodynamic, runoff simulation and flood mapping methods used in the study represented a general case study of the integration of hydrological and multi-source spatial information for flood forecasting and mapping. The datasets compiled over the course of the project provide useful information as a guideline for the implementation of other multi models and multi-source data in an integrated operational flood forecasting system. The developed QPF model is flexible enough to be easily extended for short–range severe flood forecasting over medium and large river basins in other tropical area.

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