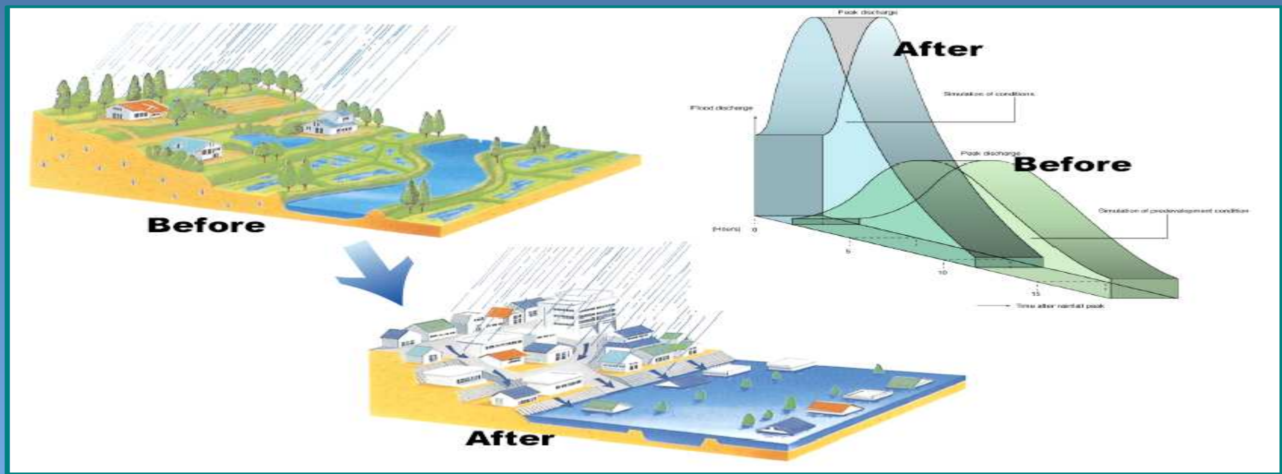
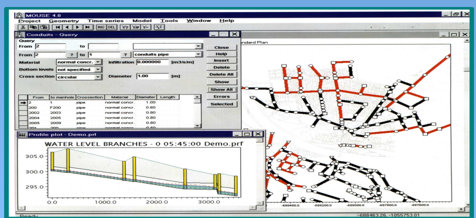
National Taiwan University

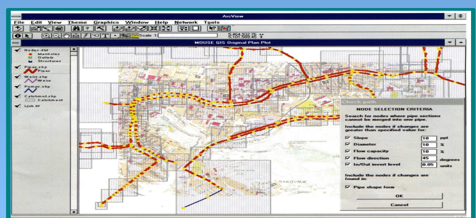
Hydropredict2012

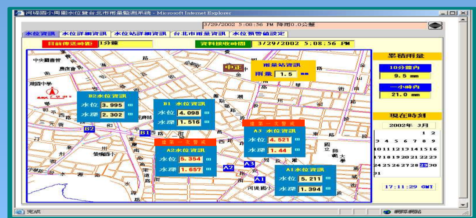
Multi-step-ahead inflow forecasting for reservoir operation and management in mountainous areas

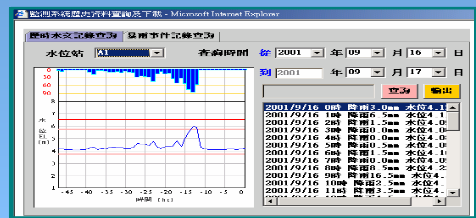
Fi-John Chang*, MJ Tsai, LC Chang, WF Yang







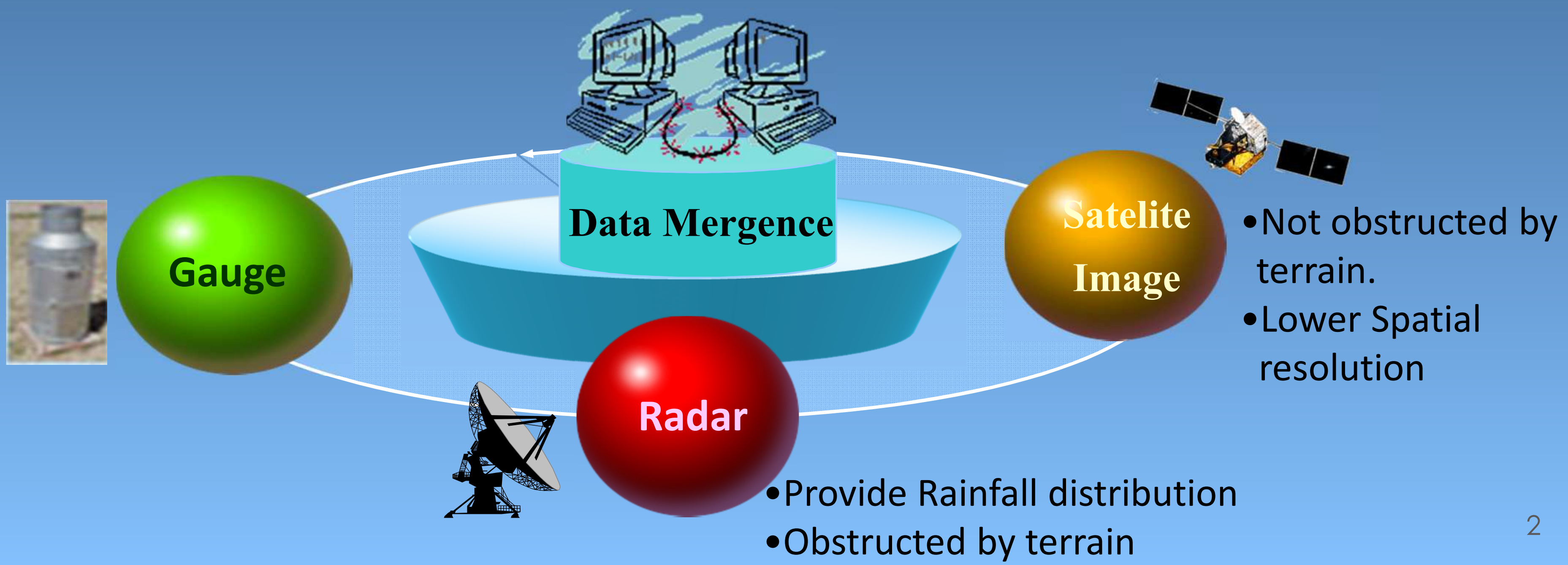




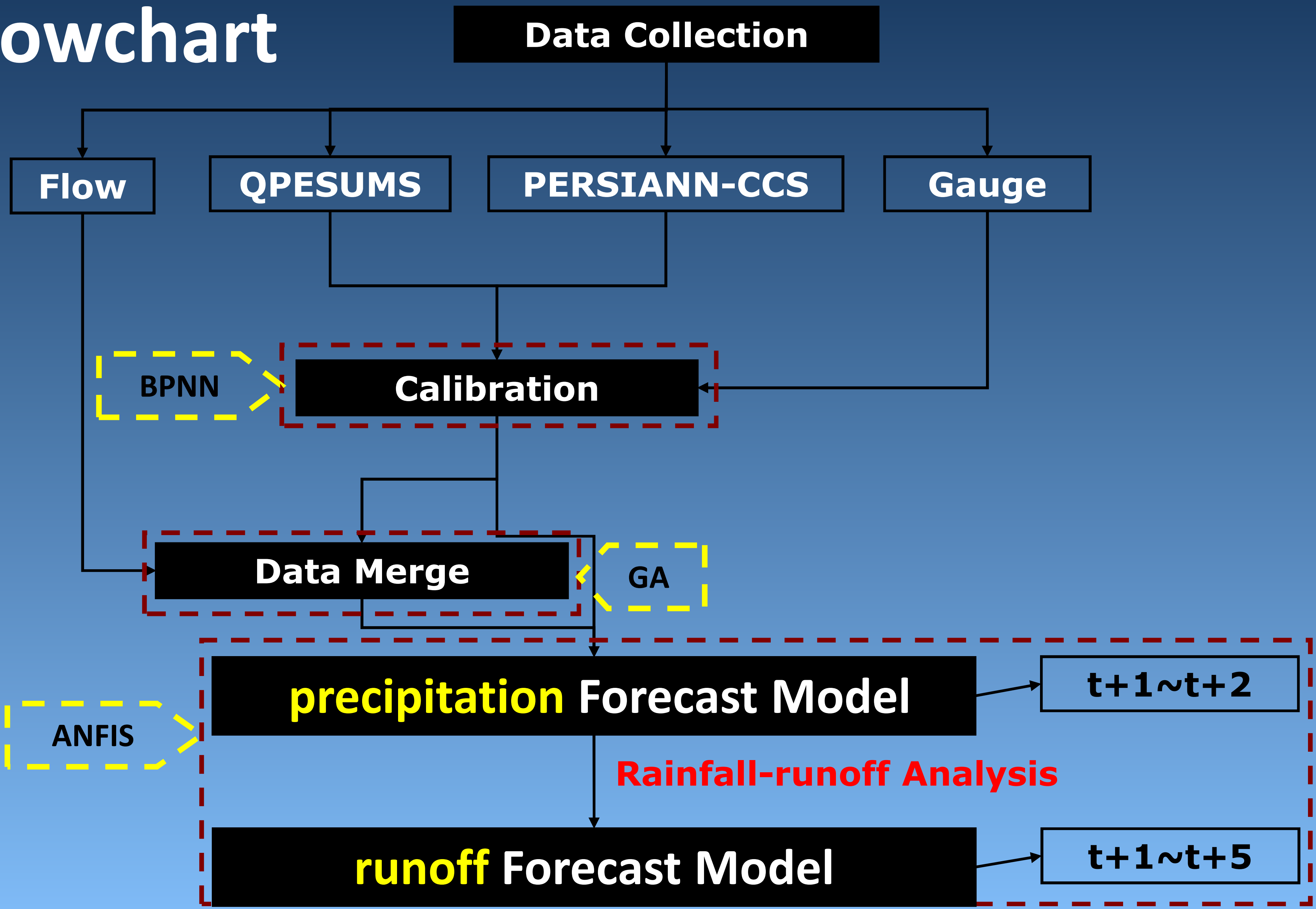
Multi-step ahead inflow forecasting has a critical role in reservoir operation during typhoons.

We develop a novel semi-distributed, data-driven, rainfall-runoff model for reservoir.

An Adaptive Network-based Fuzzy Inference System (ANFIS) is created using multiple information.



Flowchart



Data Collection
Flow
QPESUMS
PERSIANN-CCS
Gauge
BPNN
Calibration
Data Merge
GA
ANFIS
precipitation Forecast Model
t+1~t+2
Rainfall-runoff Analysis
runoff Forecast Model
t+1~t+5

Taiwan

- **Area:36000km2   Population:24 M**

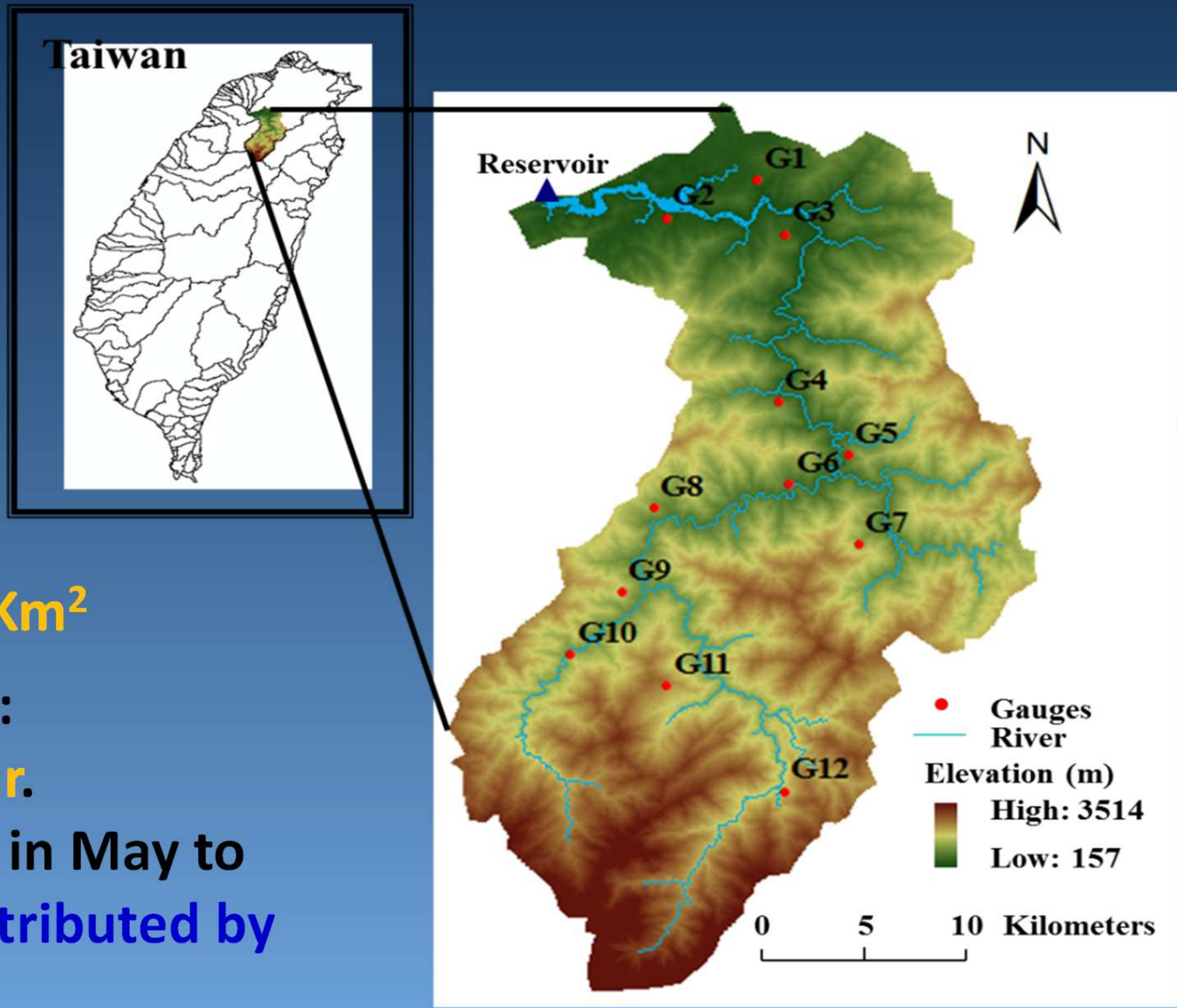
- **Rainfall**
  - **Annual rainfall: 2,500 mm**
  - **2.5 times the world average**
- **Runoff**
  - **river: short and steep**
- **Typhoons**

  Last century about 350 Typhoons


Touch Your Heart
http://taiwan.net.tw
比・想・像・中・更・精・彩
台灣
台灣水果有GO讚

Study Area--

Shihmen reservoir

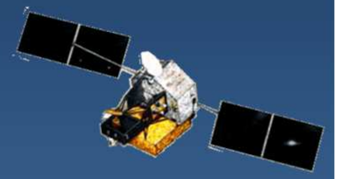


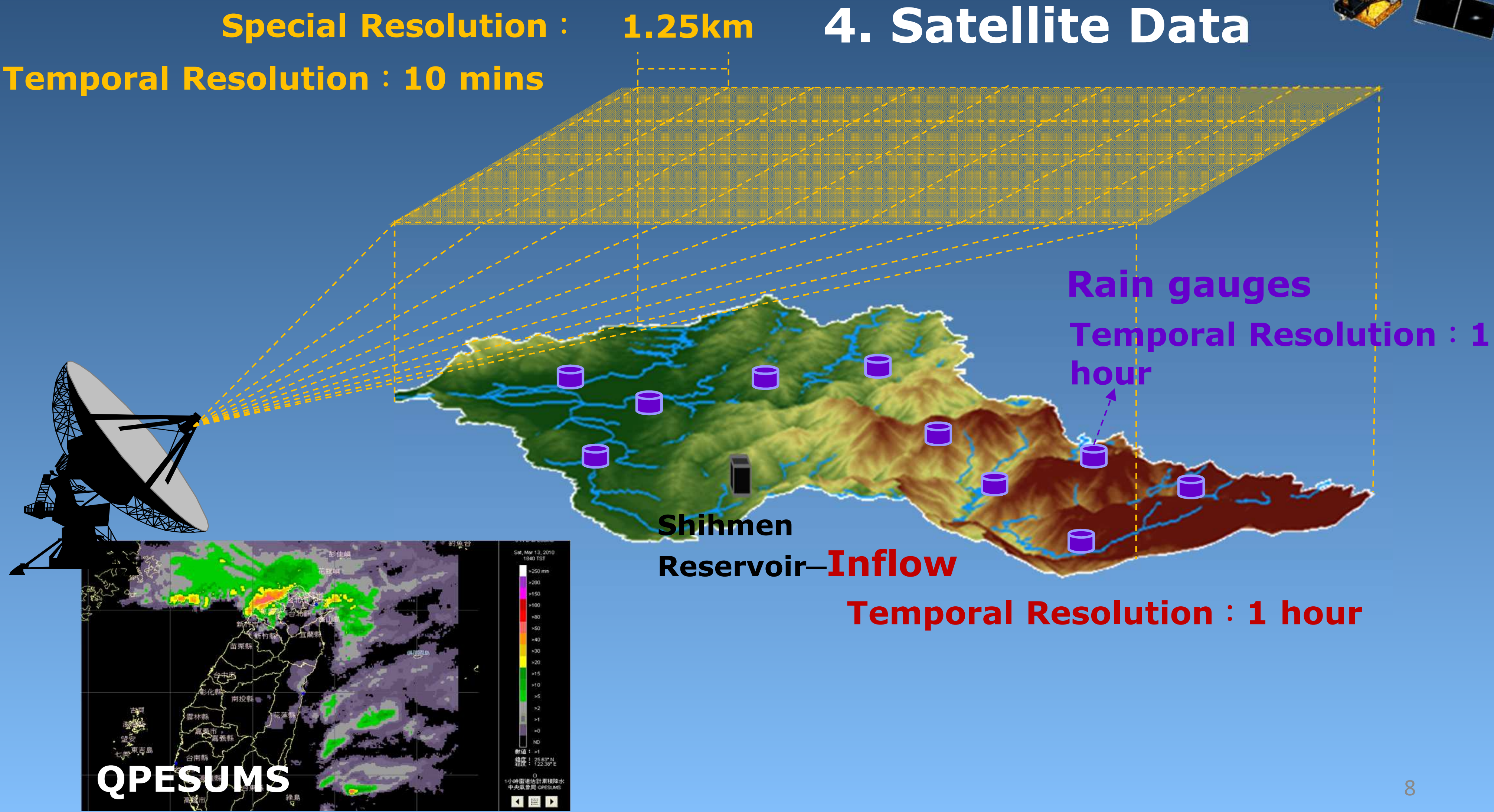
- **Catchment area :763.4 Km^2**
- **Annual average rainfall :**
  2,200 to 2,800 mm/year.
- **Most of rainfall happen in May to September mainly contributed by Typhoons.**

Data Collection

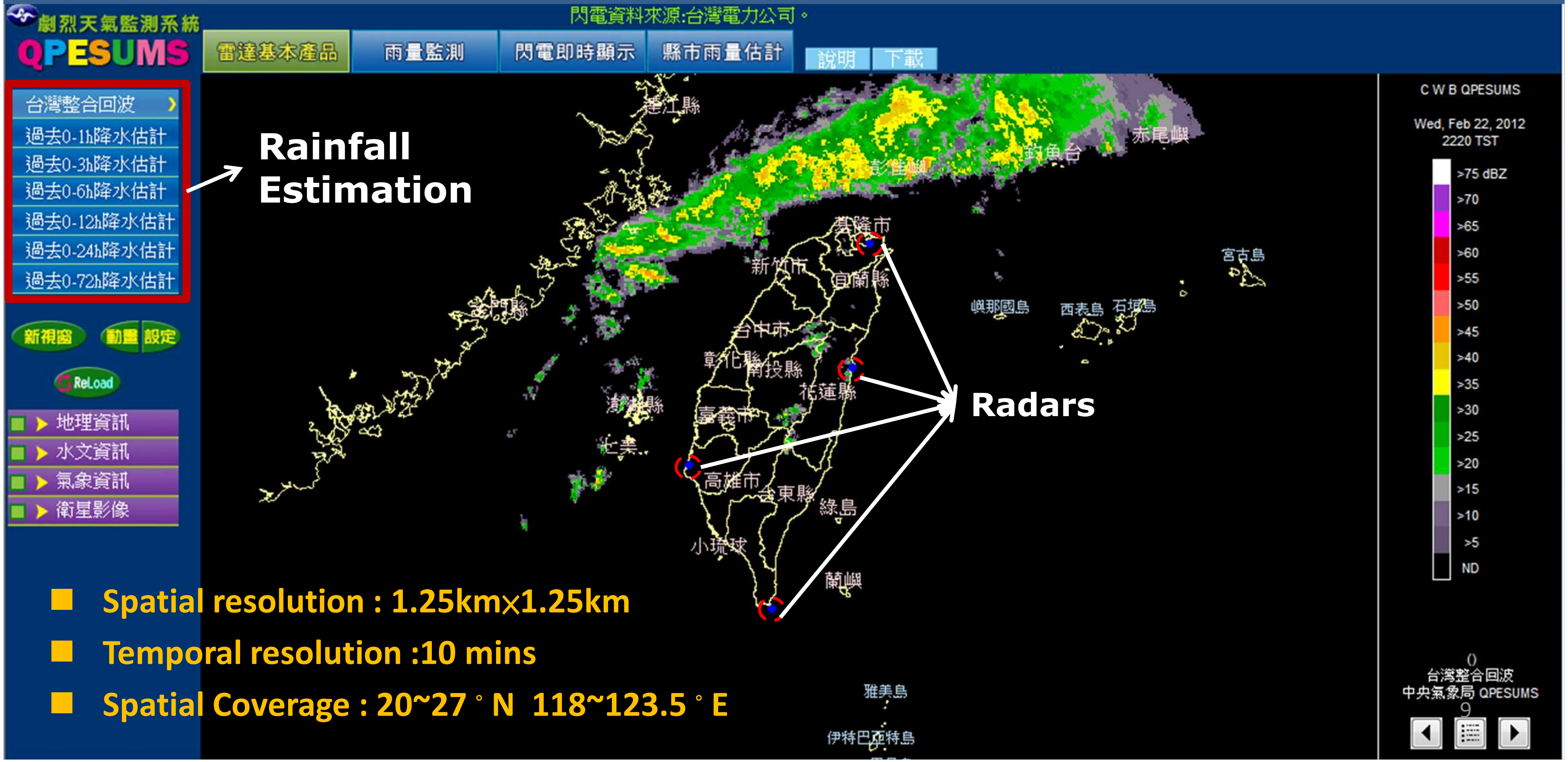
Data Collection：

1. Inflow
2. Rain gauges
3. Radar Data
4. Satellite Data



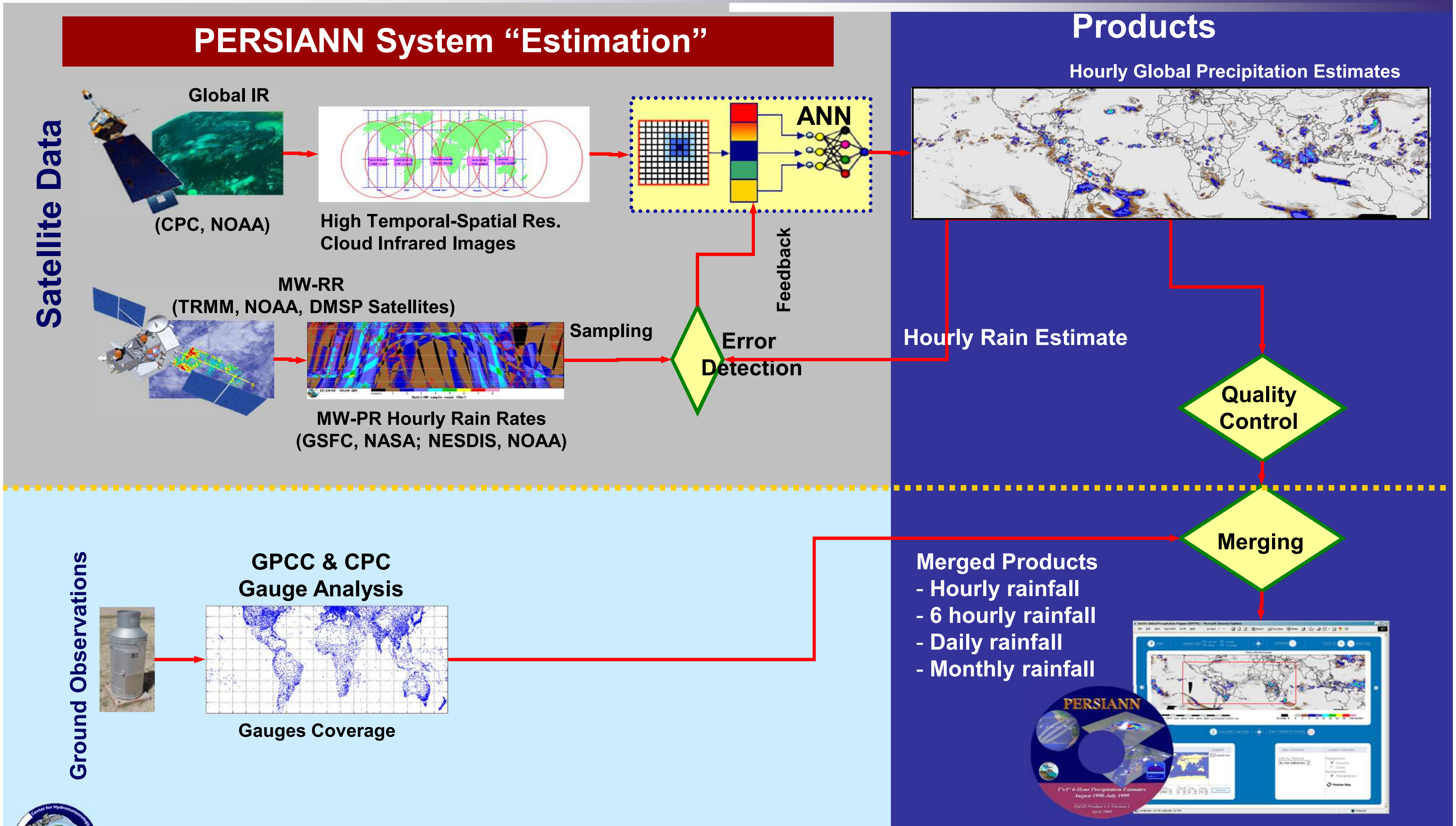


Quantitative Precipitation Estimation and Segregation Using Multiple Sensors (QPESUMS)



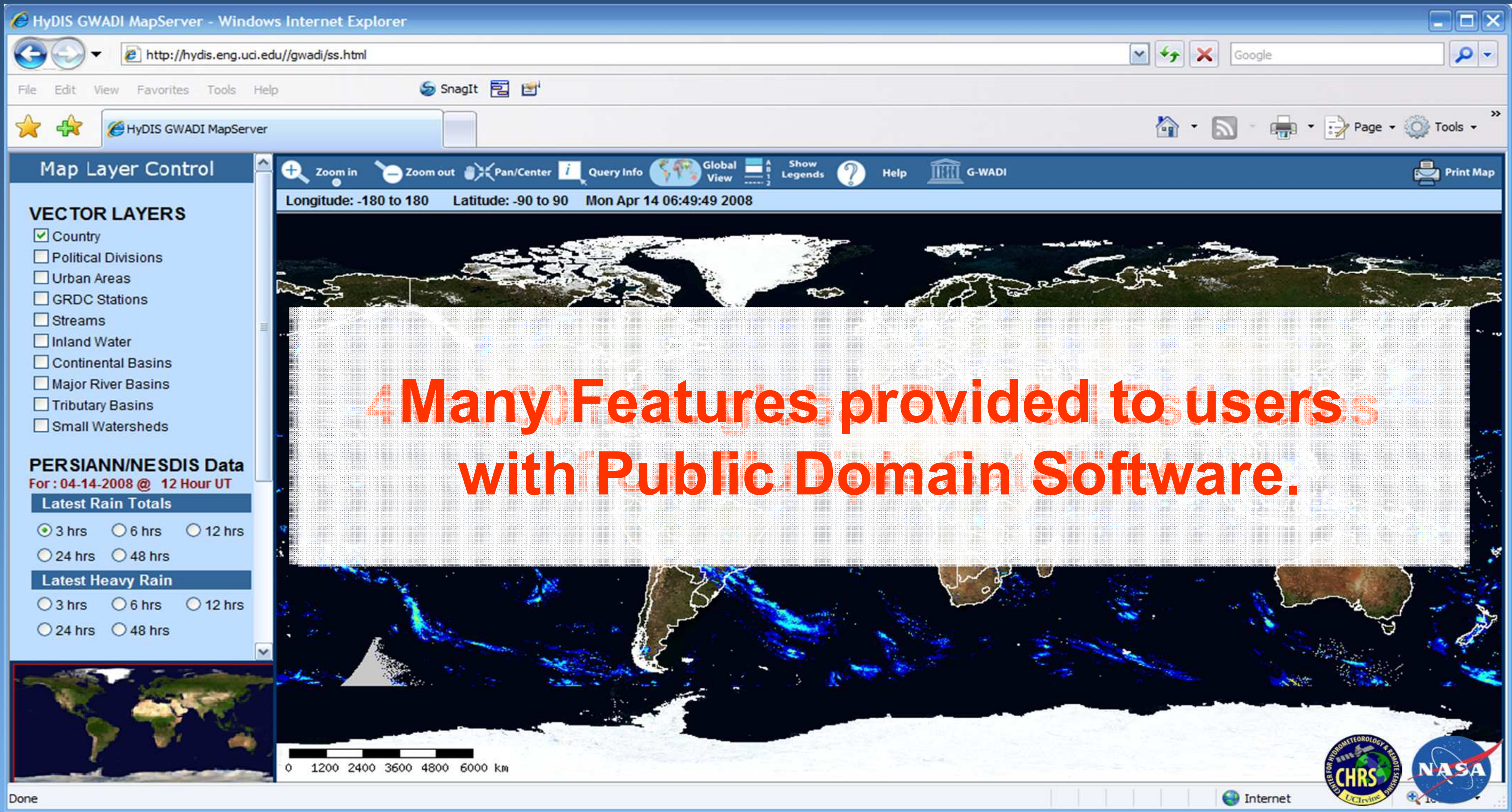
- Spatial resolution : 1.25km×1.25km
- Temporal resolution :10 mins
- Spatial Coverage : 20~27゜N 118~123.5゜E

Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN)



Center for Hydrometeorology and Remote Sensing, University of California, Irvine

Real Time Global Data: Cooperation With UNESCO



Calibration

Calibration

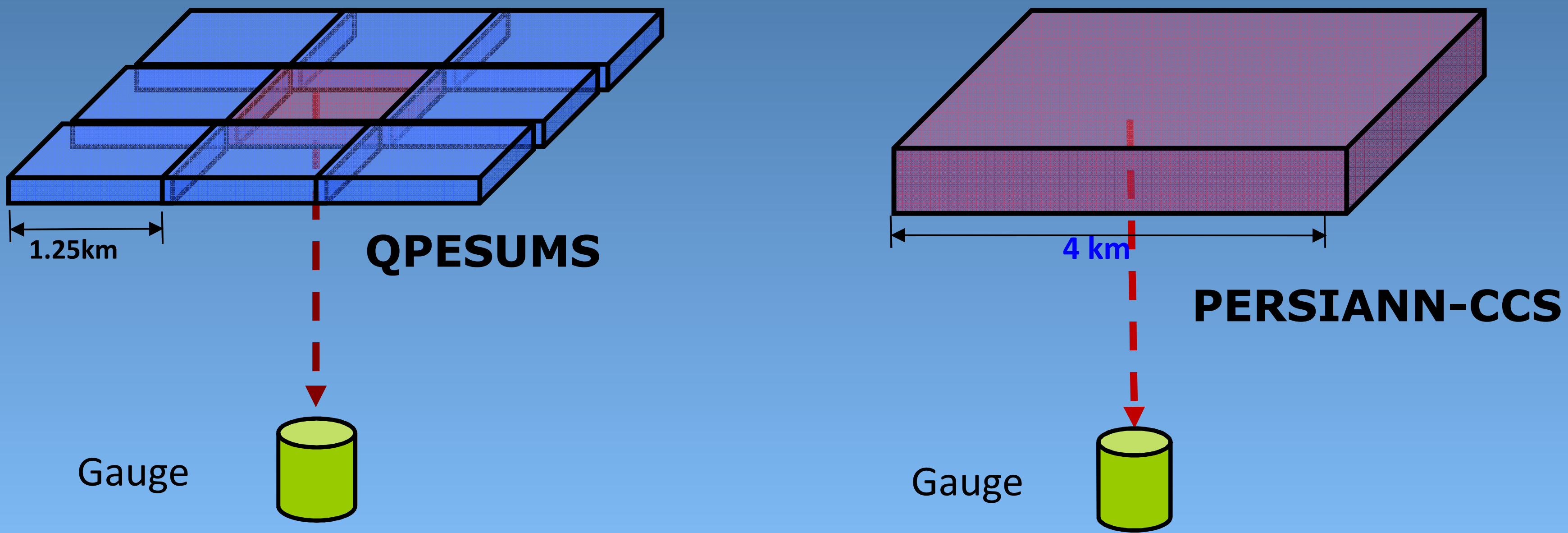
QPESUMS

Average rainfall by using 9 grids

PERSIANN-CCS

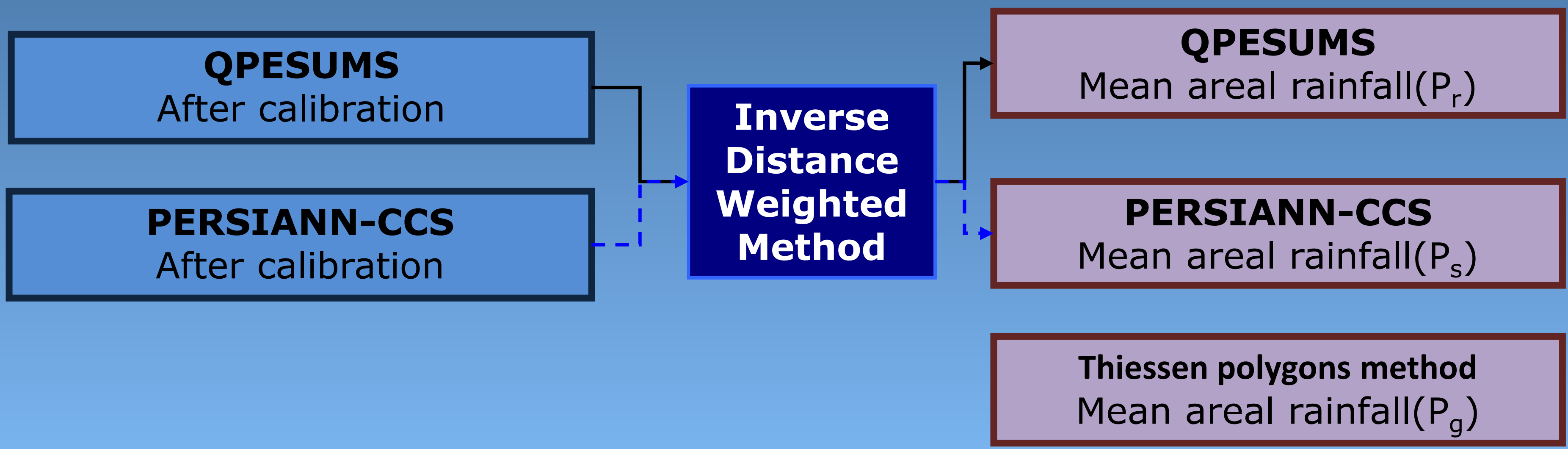
Rainfall of 1 grid

→ **BPNN** ⟷ **12 gauges**

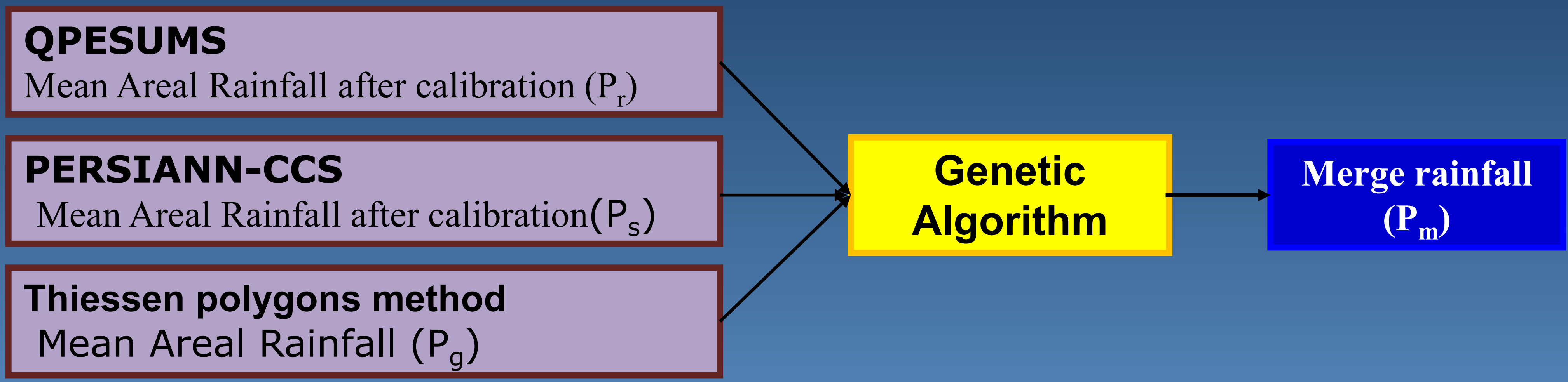


Calibration

- 13 Typhoons are collected data length is 641.
  - Train: 7 events with data length of 350.
  - Validation: 3 events with data length of 153.
  - Test: 3 events with data length of 138.

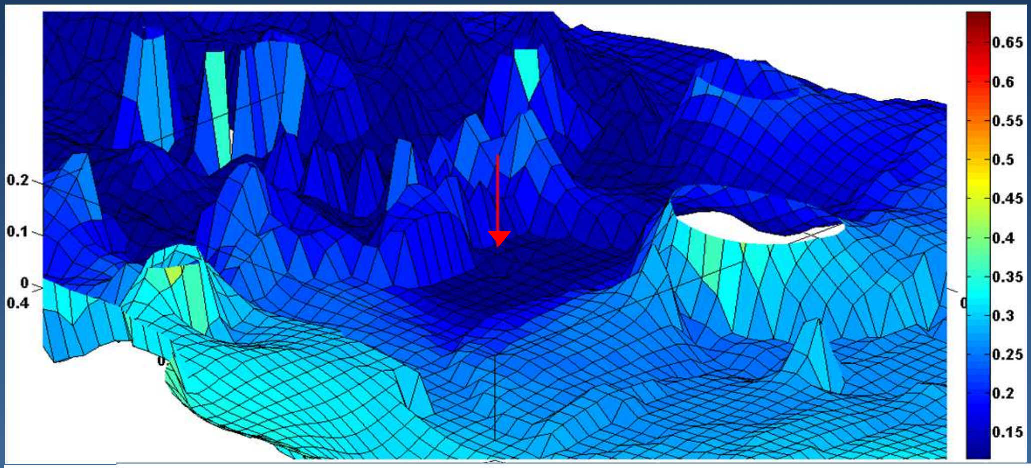


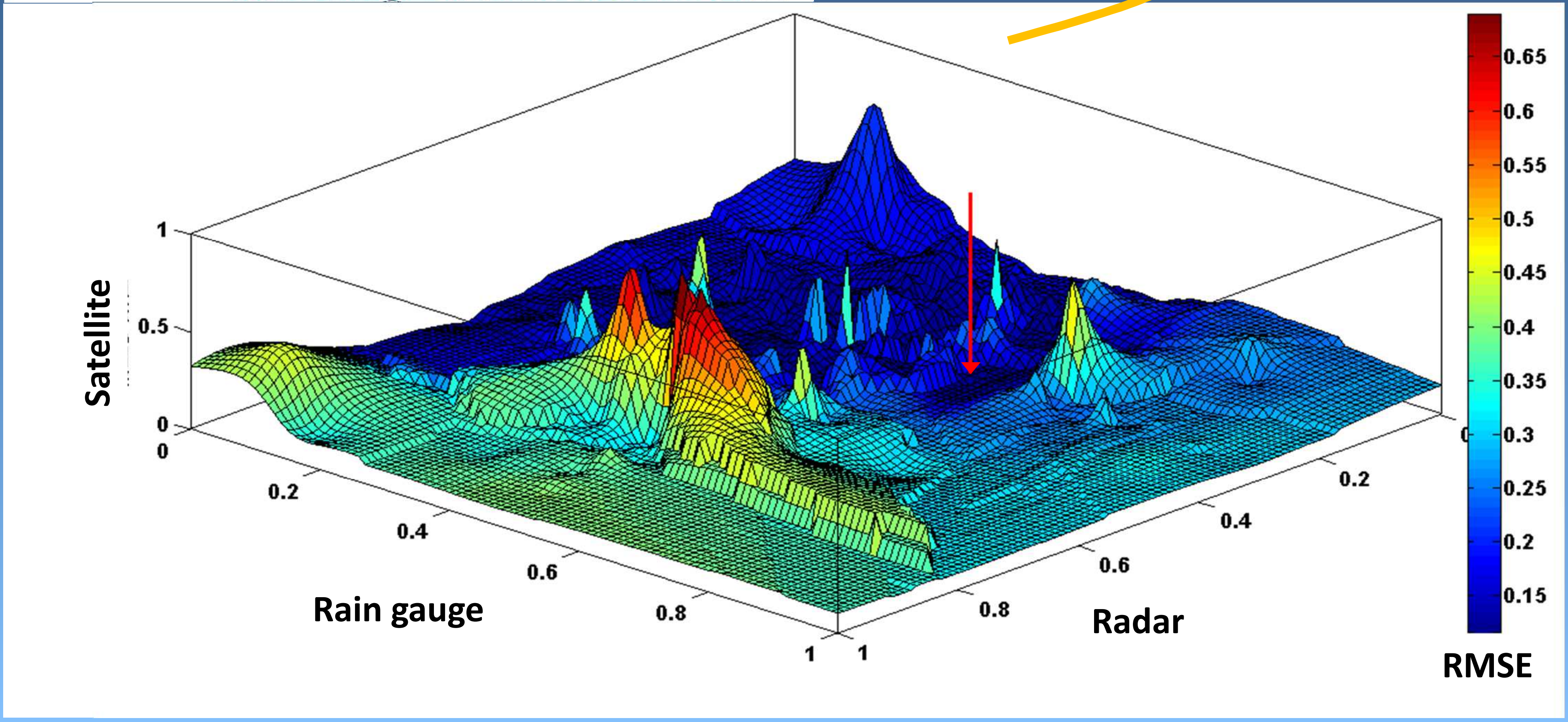
Data merge



$$Min(F) = \min\{f(X_g(t-5)\times\theta_1 + X_r'(t-5)\times\theta_2 + X_s'(t-5)\times\theta_3) - Y(t)\}$$

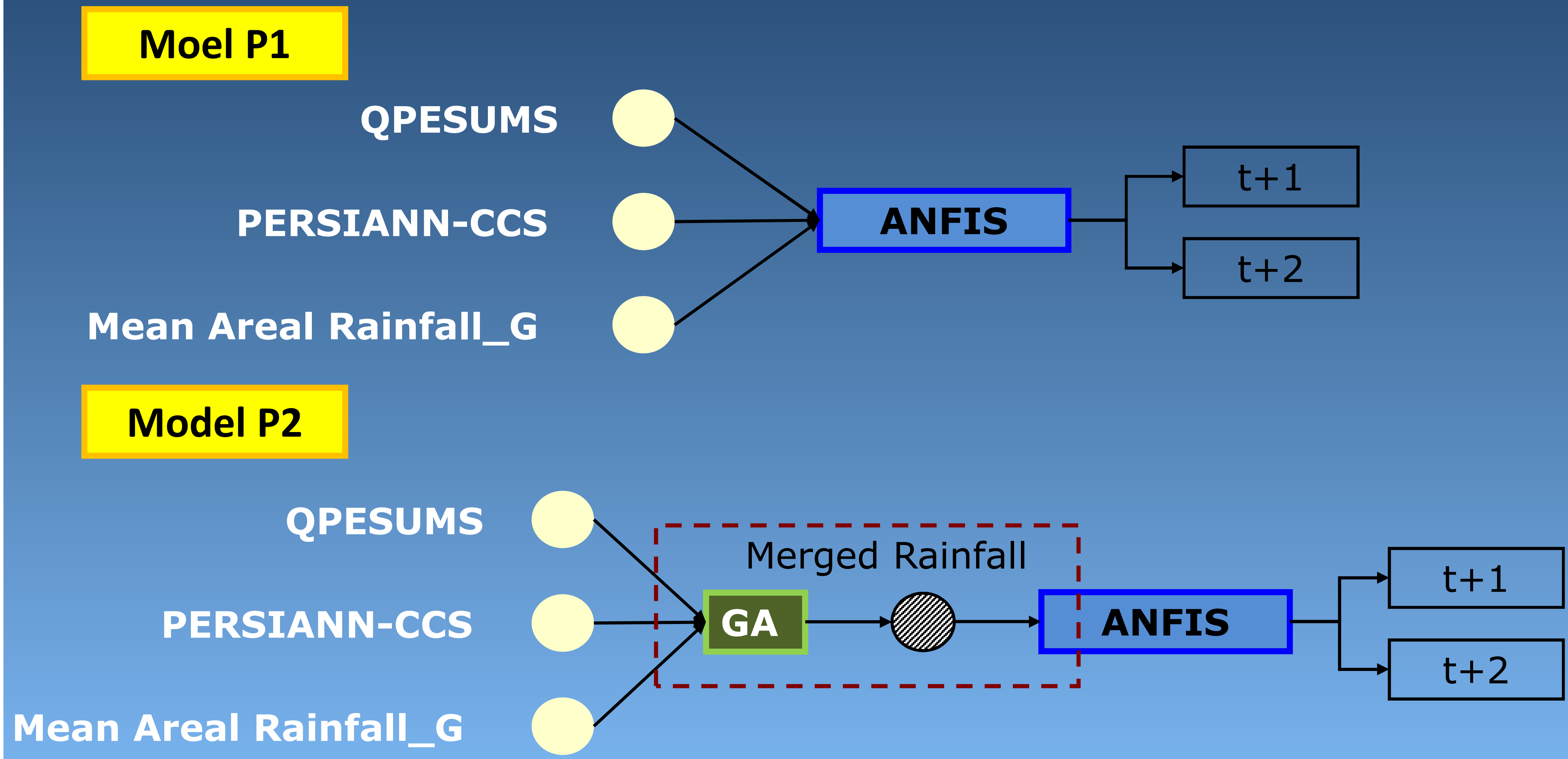
$\theta_1+\theta_2+\theta_3<=1$	θ_1	θ_2	θ_3
GA	0.56	0.30	0.06





Quantitative Precipitation Forecast Model

Quantitative Precipitation Forecast Model

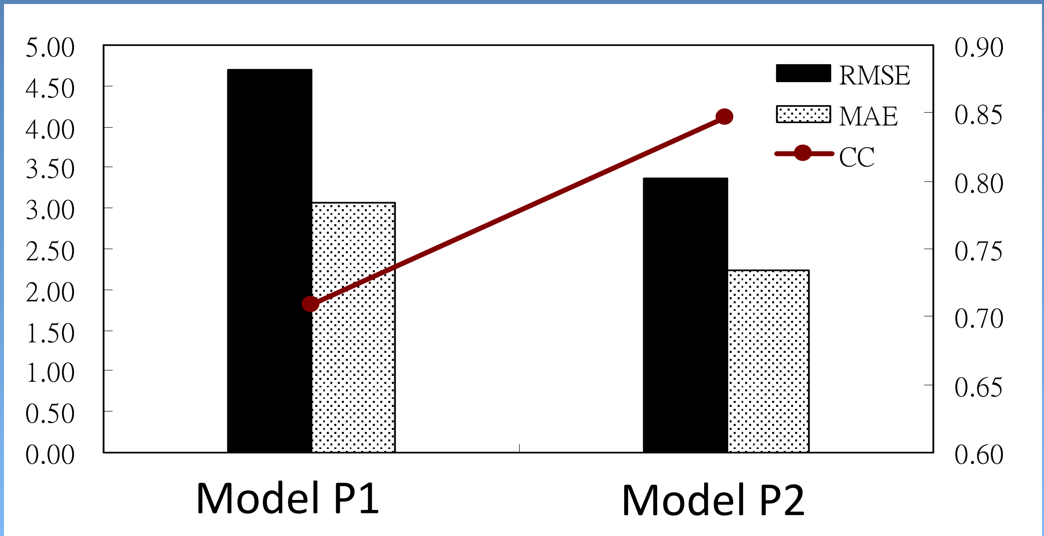


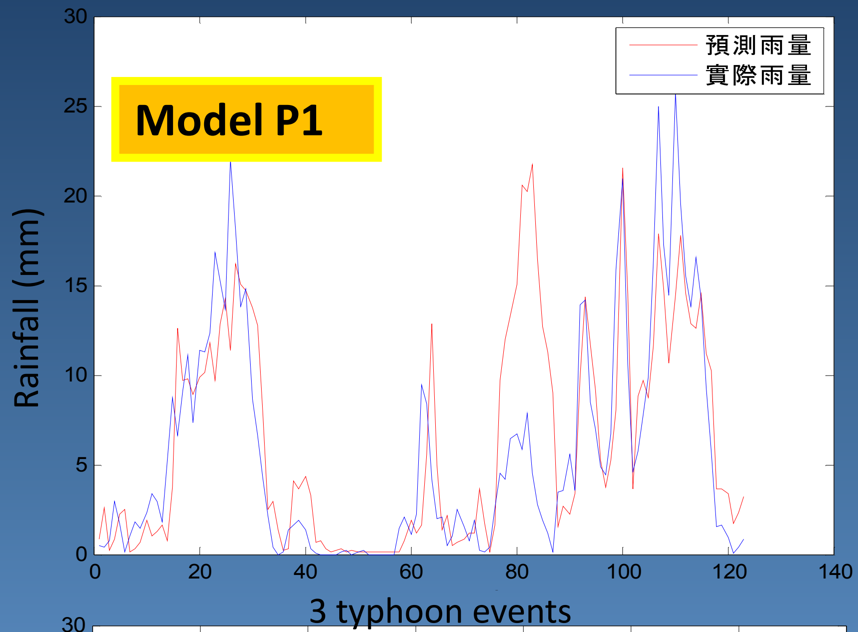
The results of QPF Model

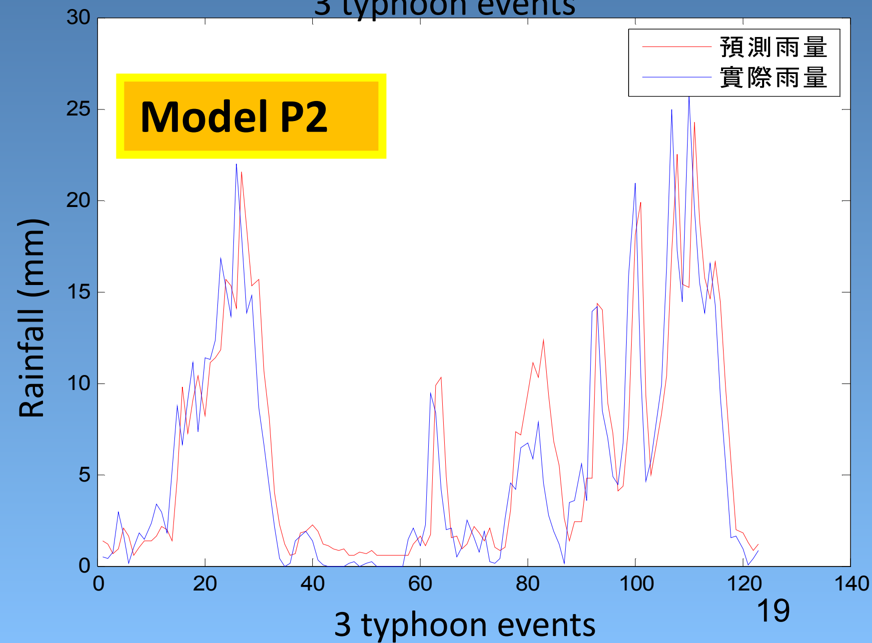
t+1

skill score (SS)

	SS
RMSE	28.23%
MAE	27.24%



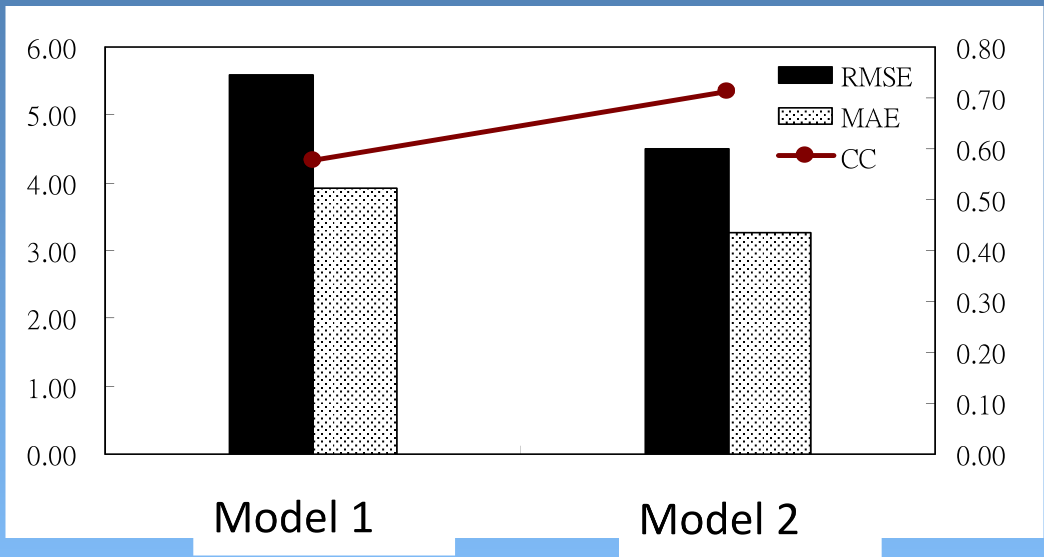


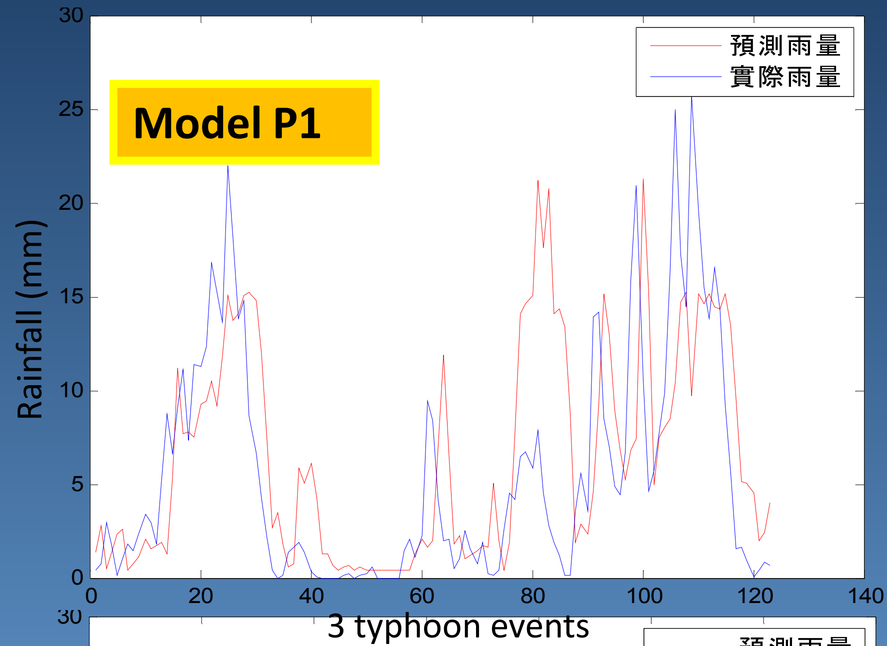


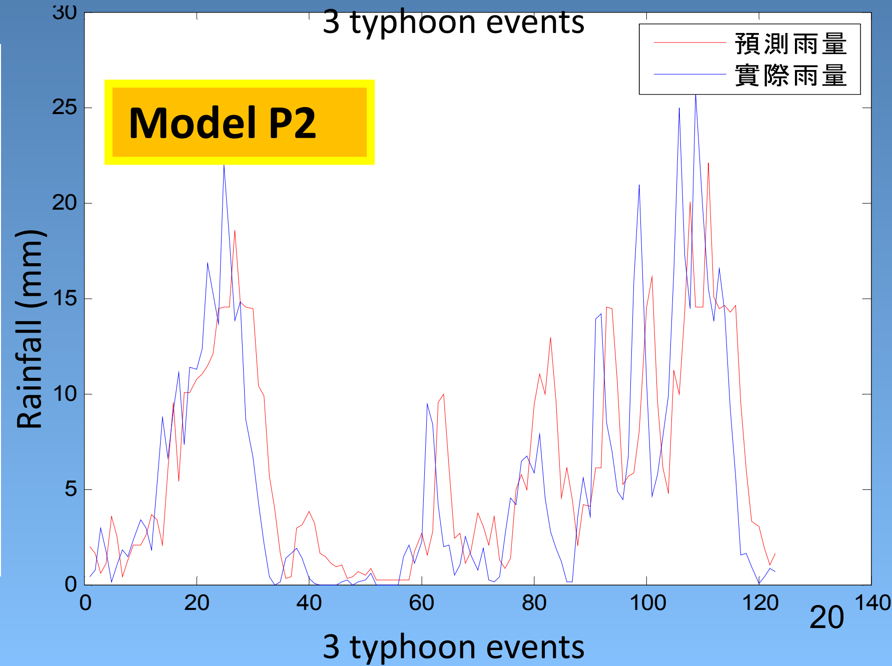
The results of QPF Model

t+2

	SS
RMSE	16.31%
MAE	16.60%

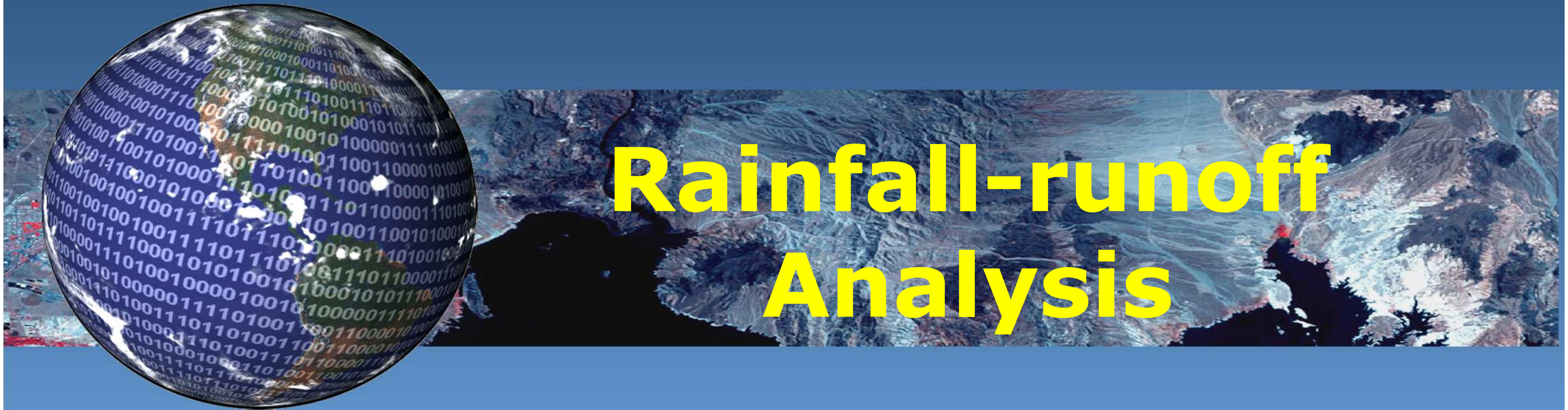






Water Resource Agency

National Taiwan University

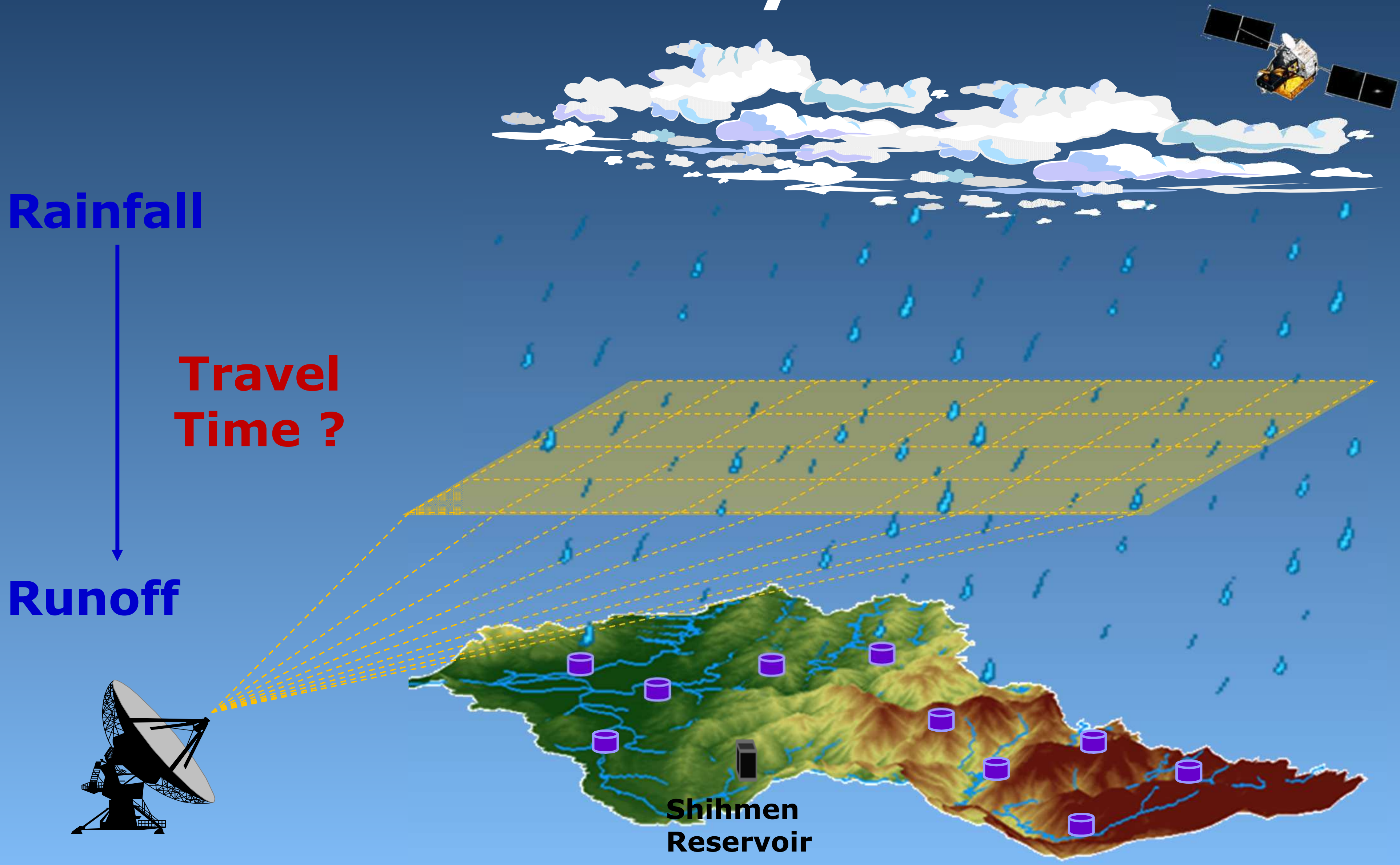


Rainfall-runoff Analysis

Inclusion of spatial distribution in a data-driven, rainfall-runoff model to improve reservoir inflow forecasting in Taiwan

in Hydrologic Process 2012

Rainfall-runoff Analysis

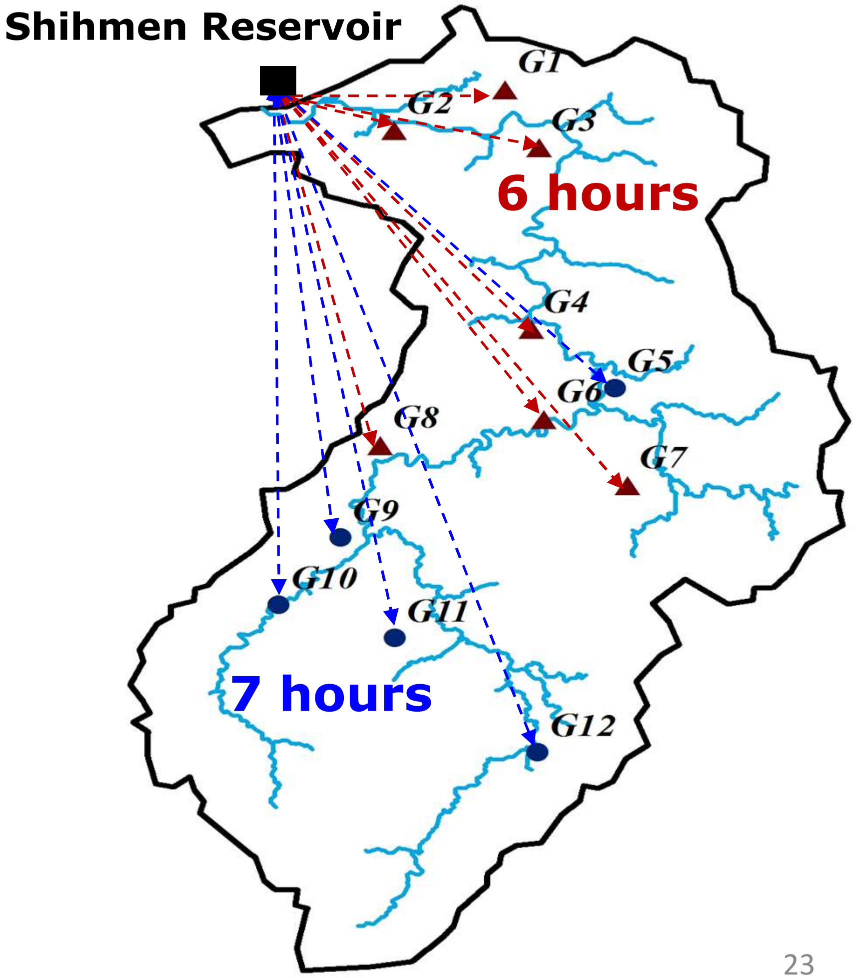


Rainfall-runoff analysis: rain gauges against reservoir inflow

Correlation Analysis:

a) Calculate correlation coefficient
   - 12 gauges
   - 11 inflow travel times (t~t-10)
   - 8 individual typhoon events

b) Select the travel time based on the <u>maximum mean correlation coefficient</u>.



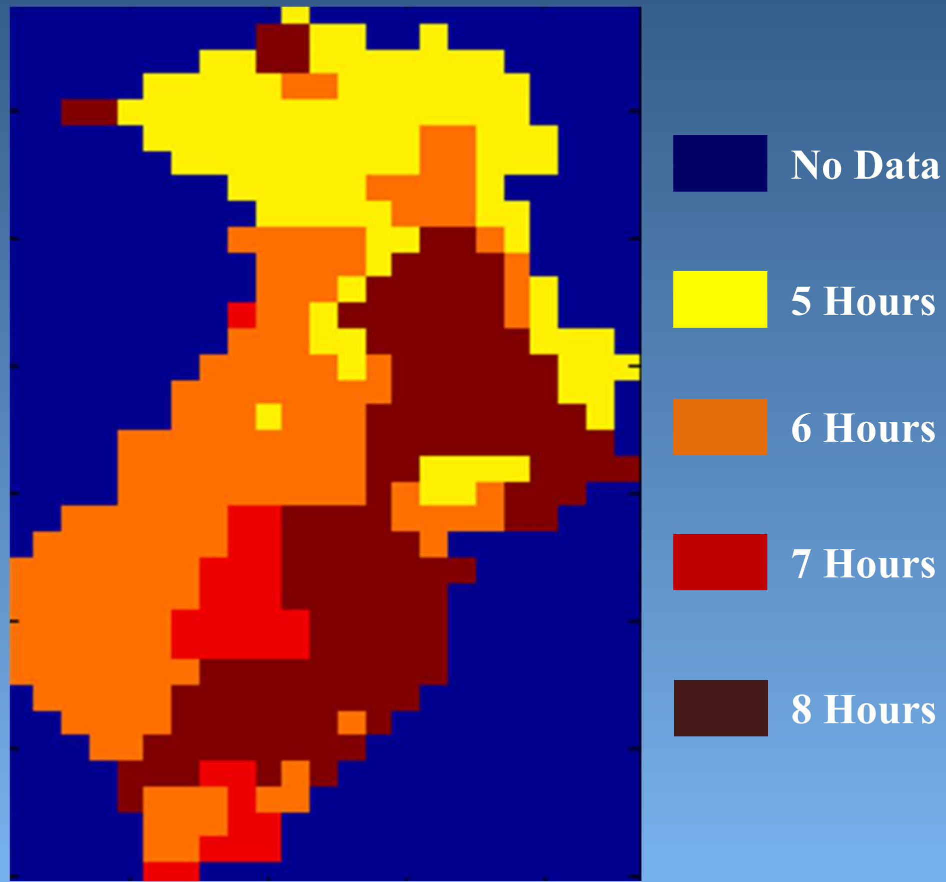
Radar data against reservoir inflow

Correlation Analysis:

a) Spatially-continuity of radar data.

b) <u>434 radar grid cells</u>

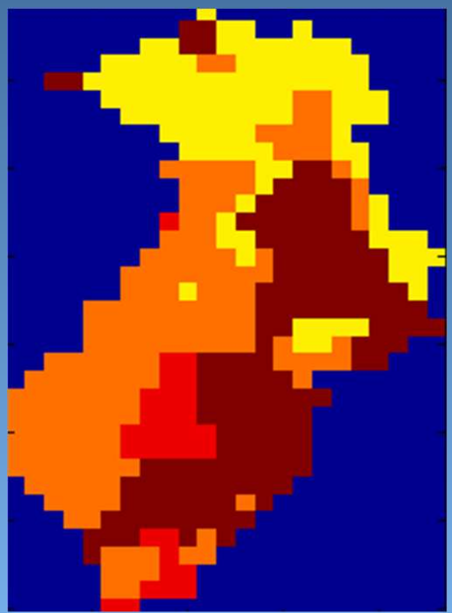
c) To prevent the development of an excessively complex solution, **spatial lumping was performed**.

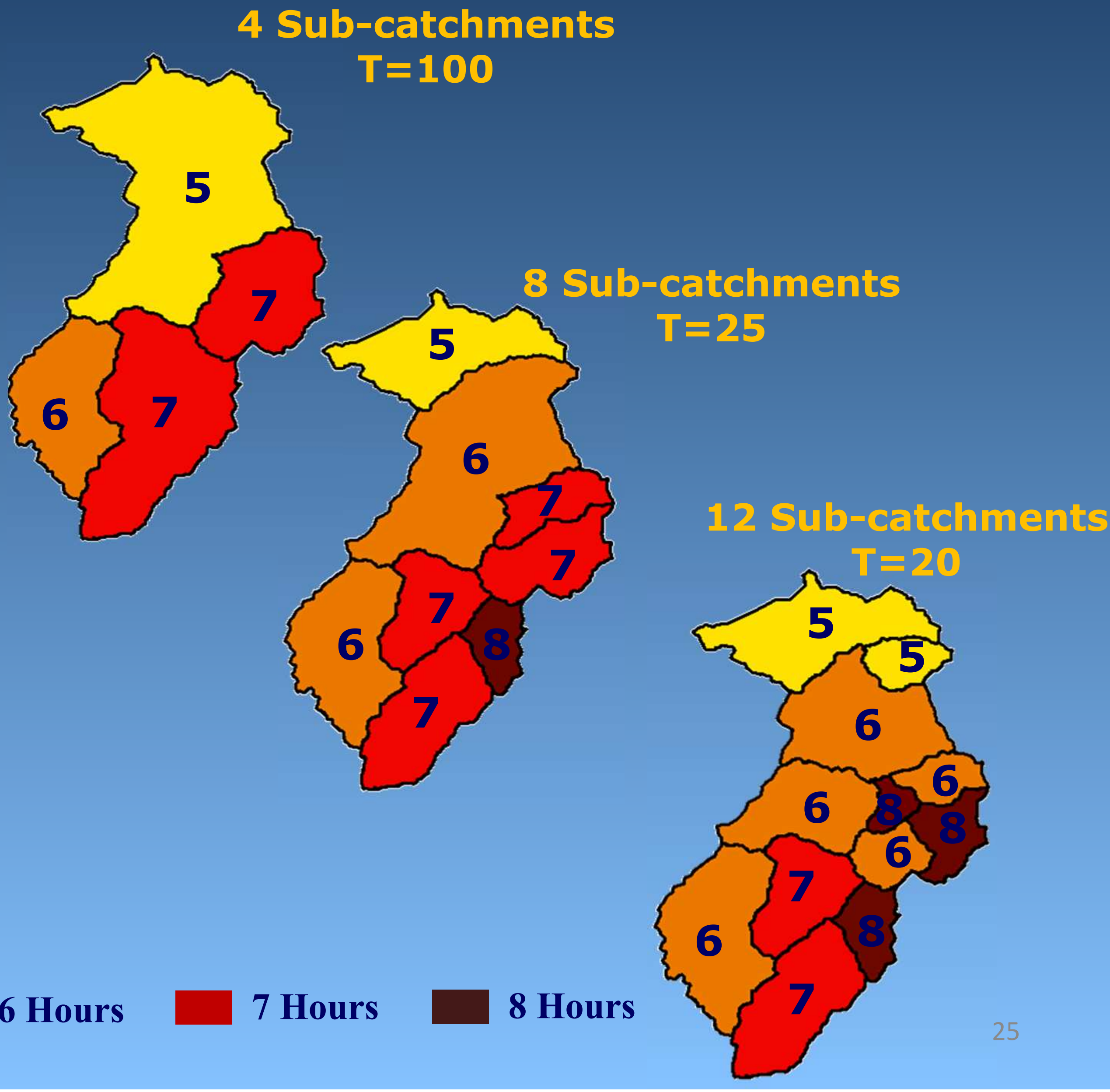


Spatial lumping by using DEM

Catchment grid

Temporal lumping

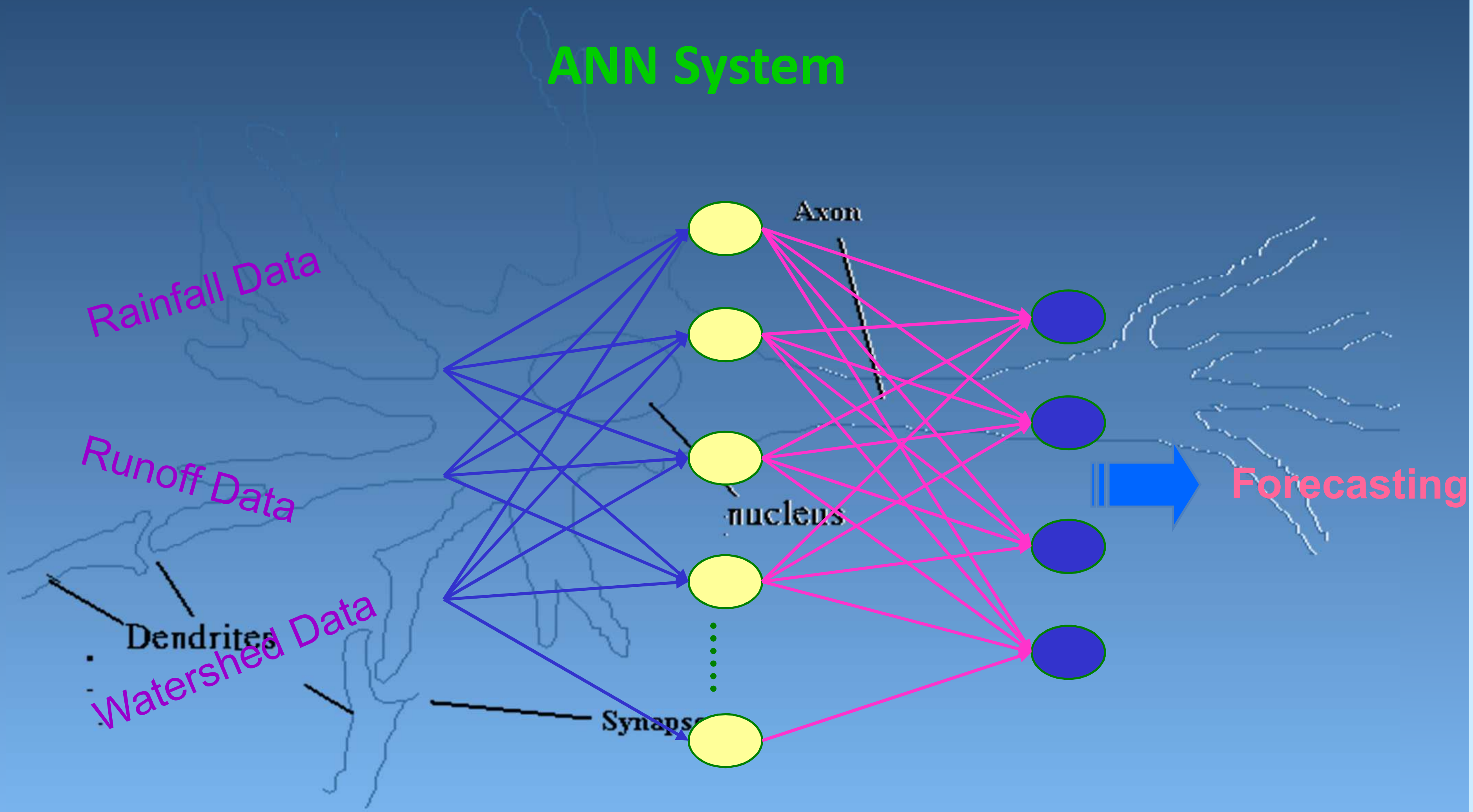




No Data | 5 Hours | 6 Hours | 7 Hours | 8 Hours

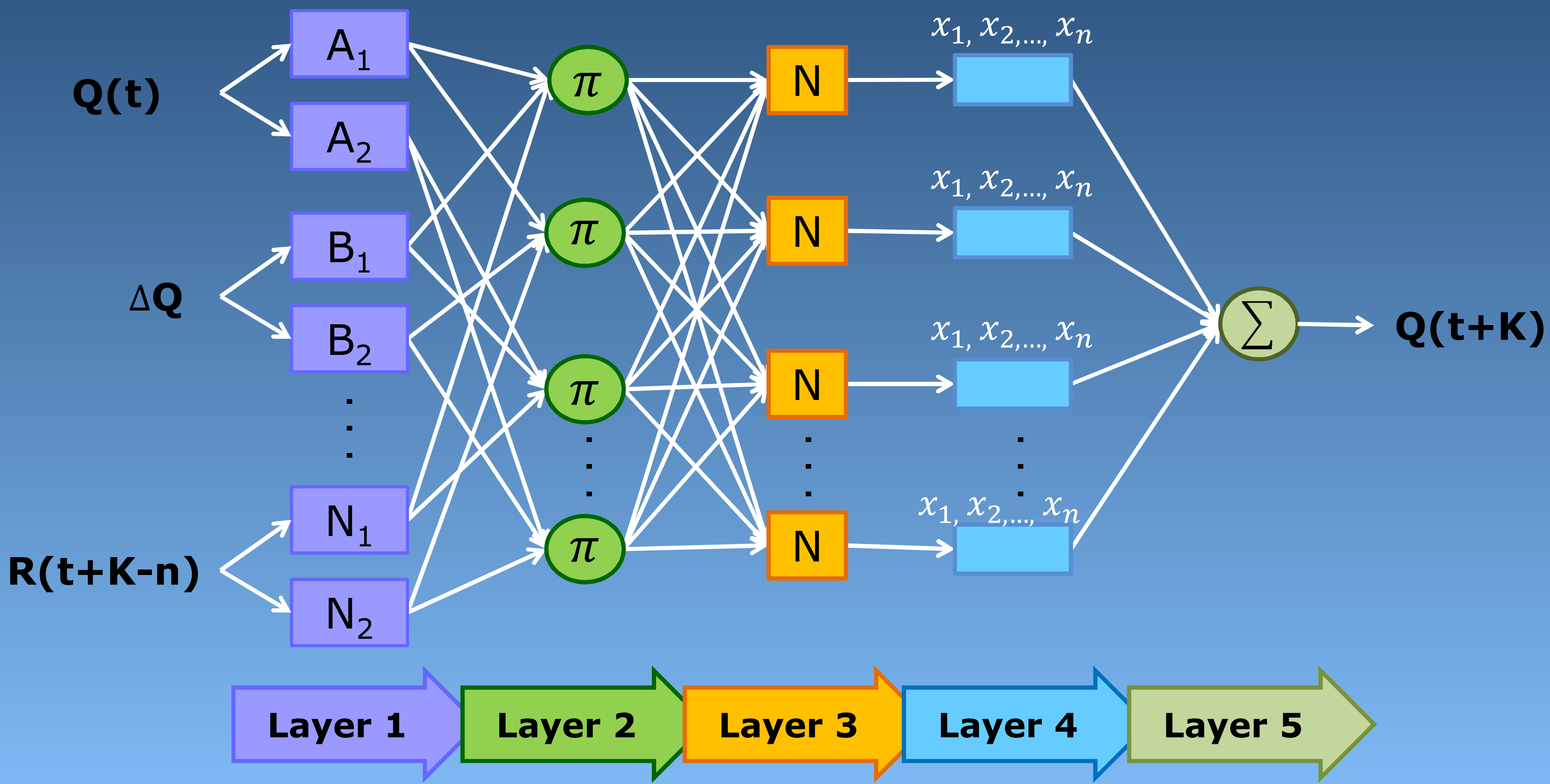
Quantitative Inflow Forecast Model

Artificial Neural Network



Inflow forecasting model - ANFIS

k = 1,2…5 and n = rainfall-runoff travel time



Structure of Model Q1 – Inflow only

- **Model Q1** : Forecasting flow at t+K (K=1~5) by using Inflow(t) and Δ Inflow

Δ Inflow=Inflow(t)-Inflow(t-1)

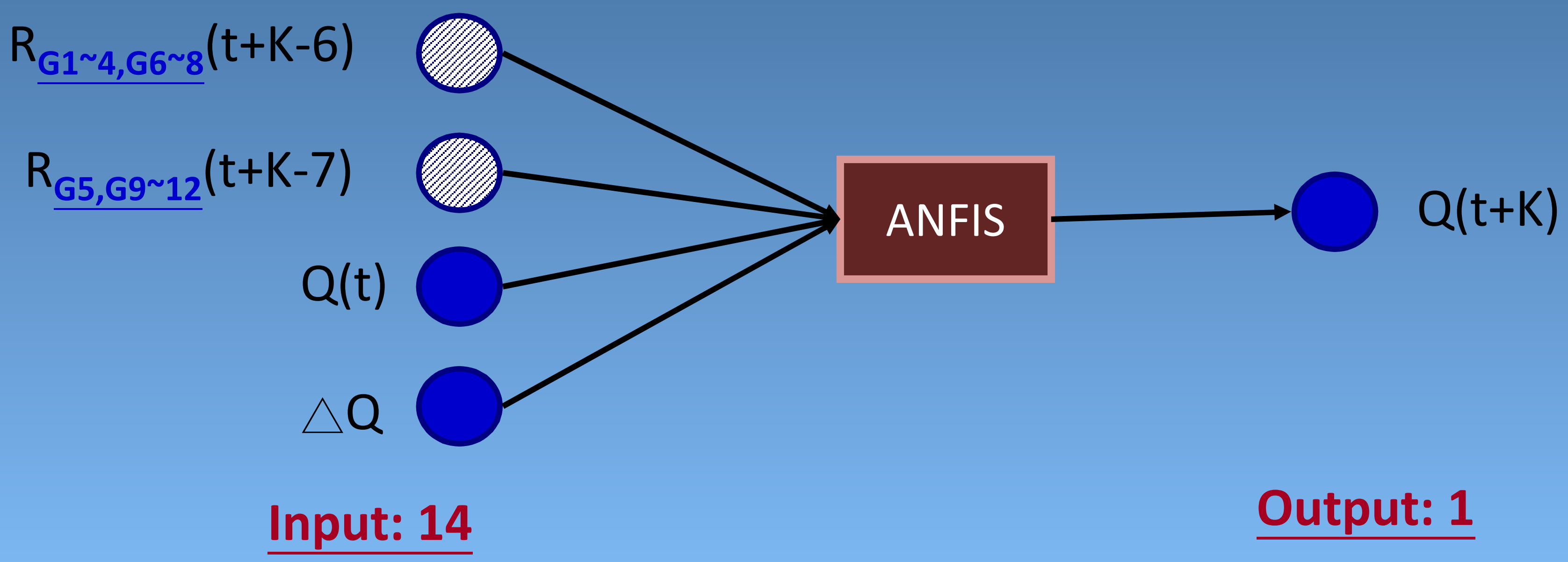
- Δ Inflow provide the trend of increase or decrease to forecasting model.

Input: 2

Output: 1

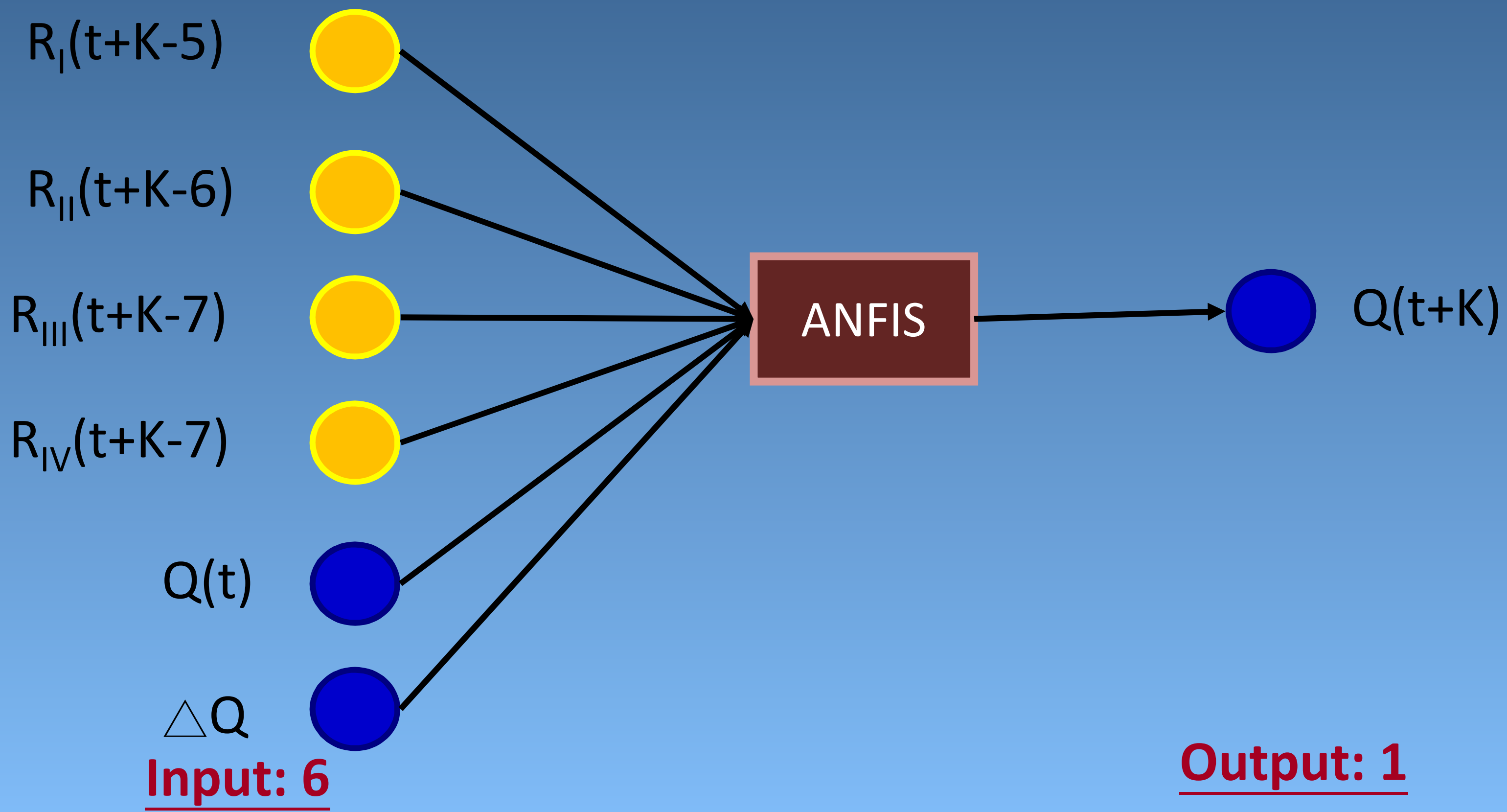
Structure of Model Q2– Inflow and Gauge rainfall

- **Model Q2**: Forecasting inflow by using rainfall of 12 gauges with different time lag, Inflow(t) and Δ Inflow.
- The time lag for 12 gauges were determined based on the result of correlation coefficient.



Structure of Model Q3 – Inflow and Radar

- **Model Q3**: Forecasting inflow by using 4 sum of the rainfall with different time lag, Inflow(t) and Δ Inflow.
- The time lag for 4 sub-catchment were determined based on the result of correlation coefficient map from **Radar Rainfall.**

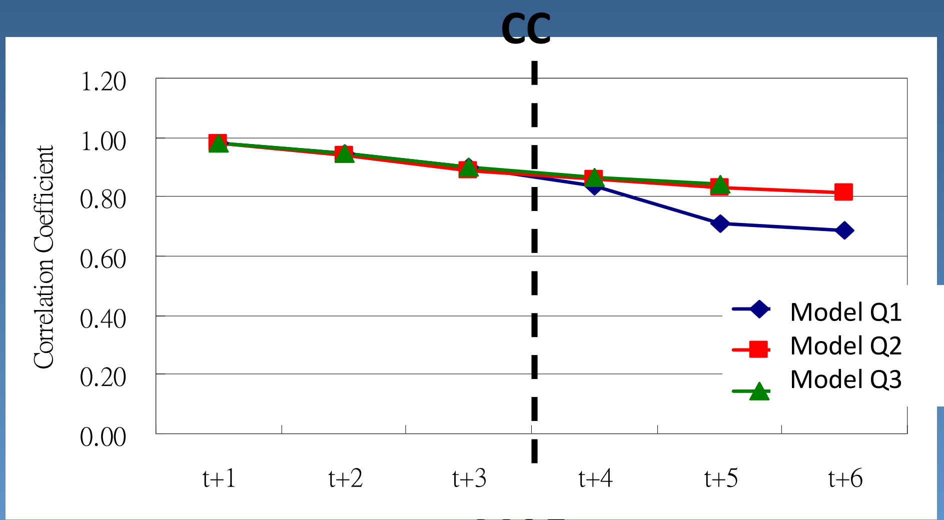


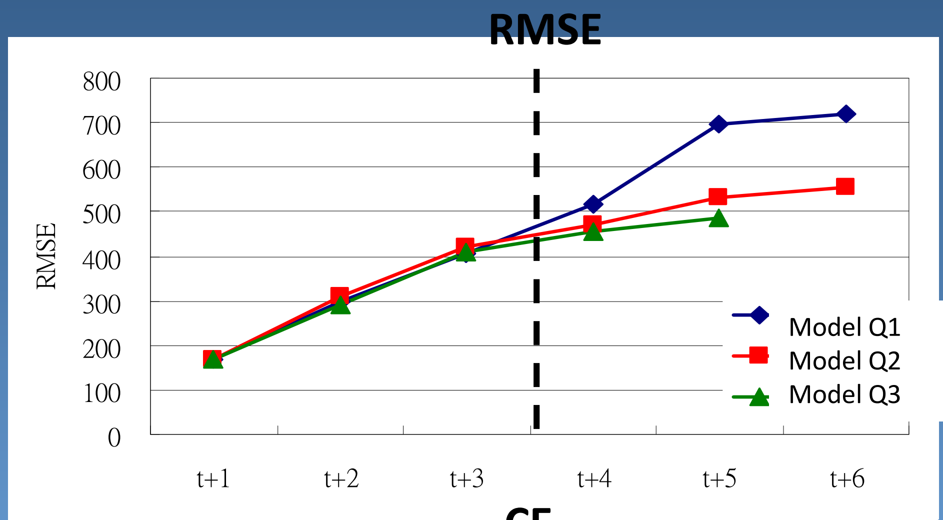
Data set

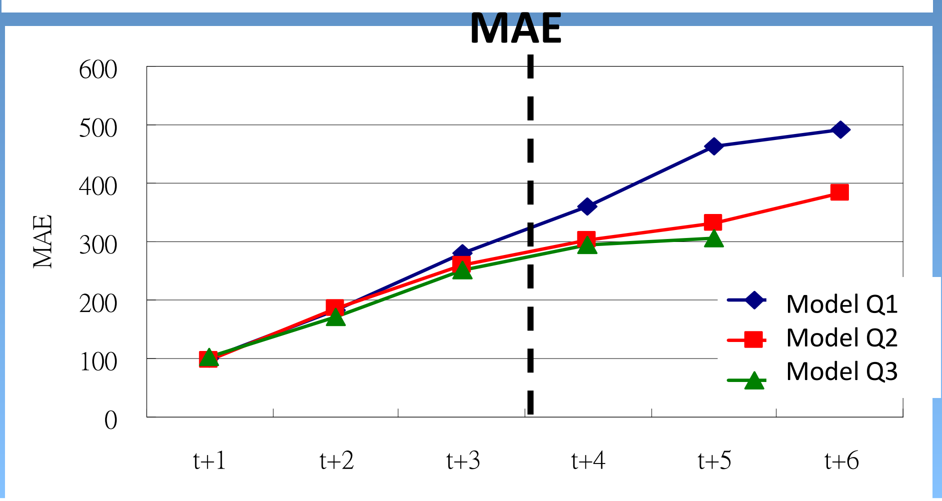
	Event	Date	Path	Peak Flow (cms)	Mean	Std.
Training	SEPAT	2007/08/16～08/19	3	1844.4	1074.09	698.22
	KROSA	2007/10/04～10/07	2	5300.39		
	KALMAEGI	2008/07/16～07/18	2	203.13		
	SINLAKU	2008/09/11～09/16	2	3351.24		
	MOROKAU	2009/08/05～08/10	3	1837.54		
Validation	WIPHA	2007/09/17～09/19	1	2788.15	1006.69	664.10
	FONG-WONG	2008/07/26～07/29	3	2039.78		
Testing	JANGMI	2008/09/26～09/29	2	3291.99	1147.78	572.91

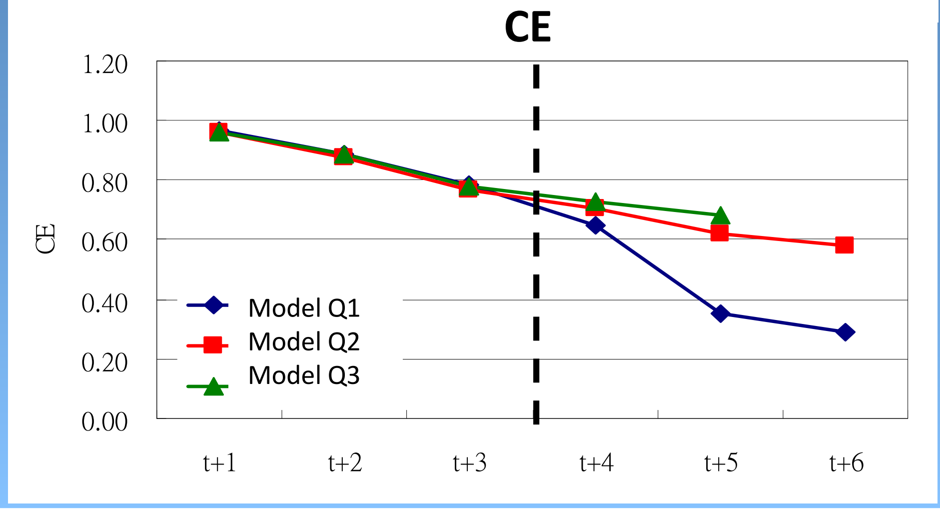
Testing results for different models

- Model Q3 has highest performance, especially when predict flow after t+4

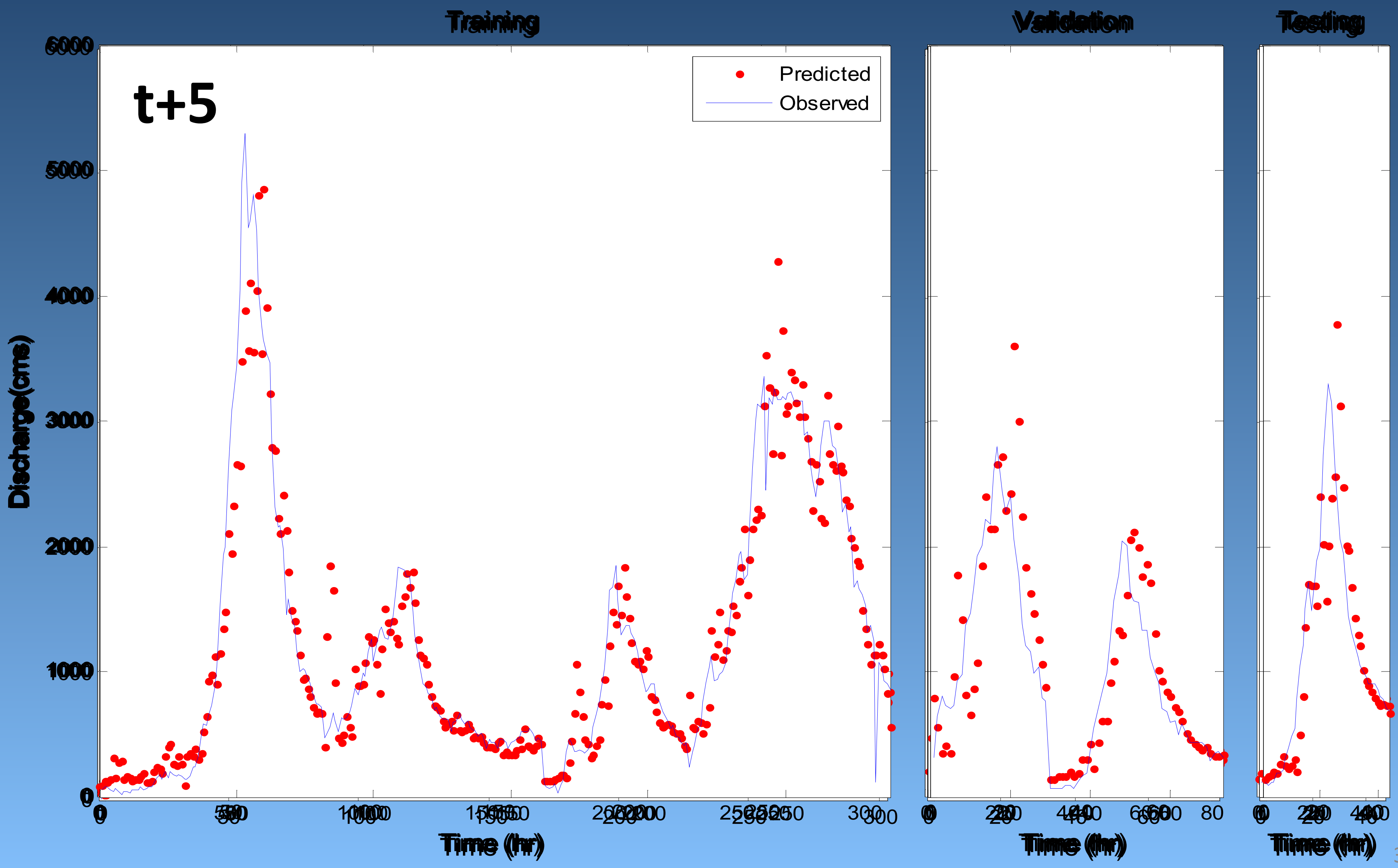




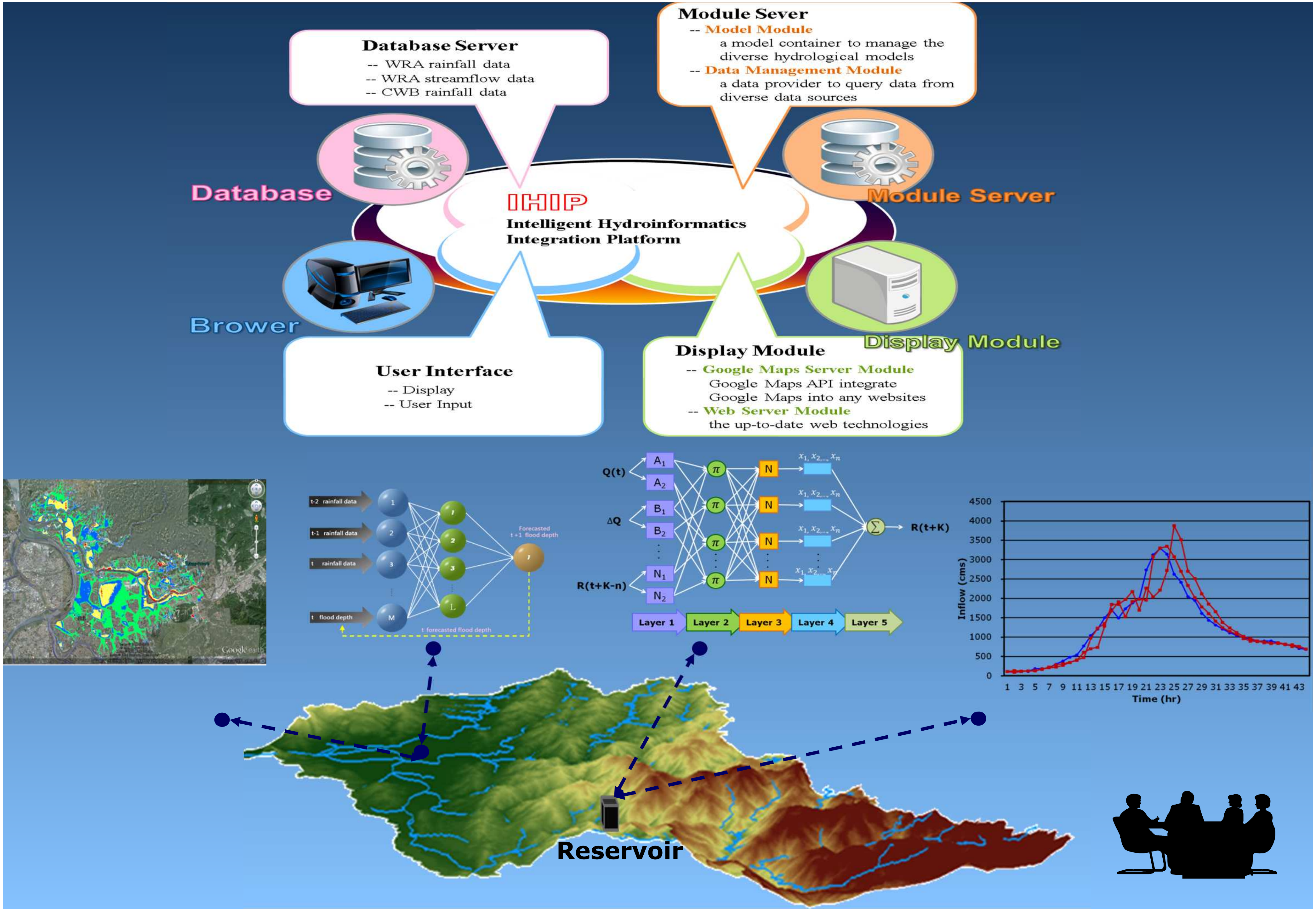




Model Q3- time series plot



An early warning system to reduce disaster risk



Module Sever
-- Model Module
a model container to manage the diverse hydrological models
-- Data Management Module
a data provider to query data from diverse data sources
Database Server
-- WRA rainfall data
-- WRA streamflow data
-- CWB rainfall data
Database
Module Server
IHIP
Intelligent Hydroinformatics Integration Platform
Brower
Display Module
User Interface
-- Display
-- User Input
Display Module
-- Google Maps Server Module
Google Maps API integrate Google Maps into any websites
-- Web Server Module
the up-to-date web technologies
t-2 rainfall data
t-1 rainfall data
t rainfall data
t flood depth
Forecasted t+1 flood depth
t forecasted flood depth
Q(t)
ΔQ
R(t+K-n)
R(t+K)
Layer 1
Layer 2
Layer 3
Layer 4
Layer 5
Inflow (cms)
Time (hr)
Reservoir

Water Resource Agency

Real time water level forecasting system

Now: 2012/09/11 16:00

Report time

2012/09/11 17:00

Google map **Figures**

Display on Google Map

Catchment:
Water level information

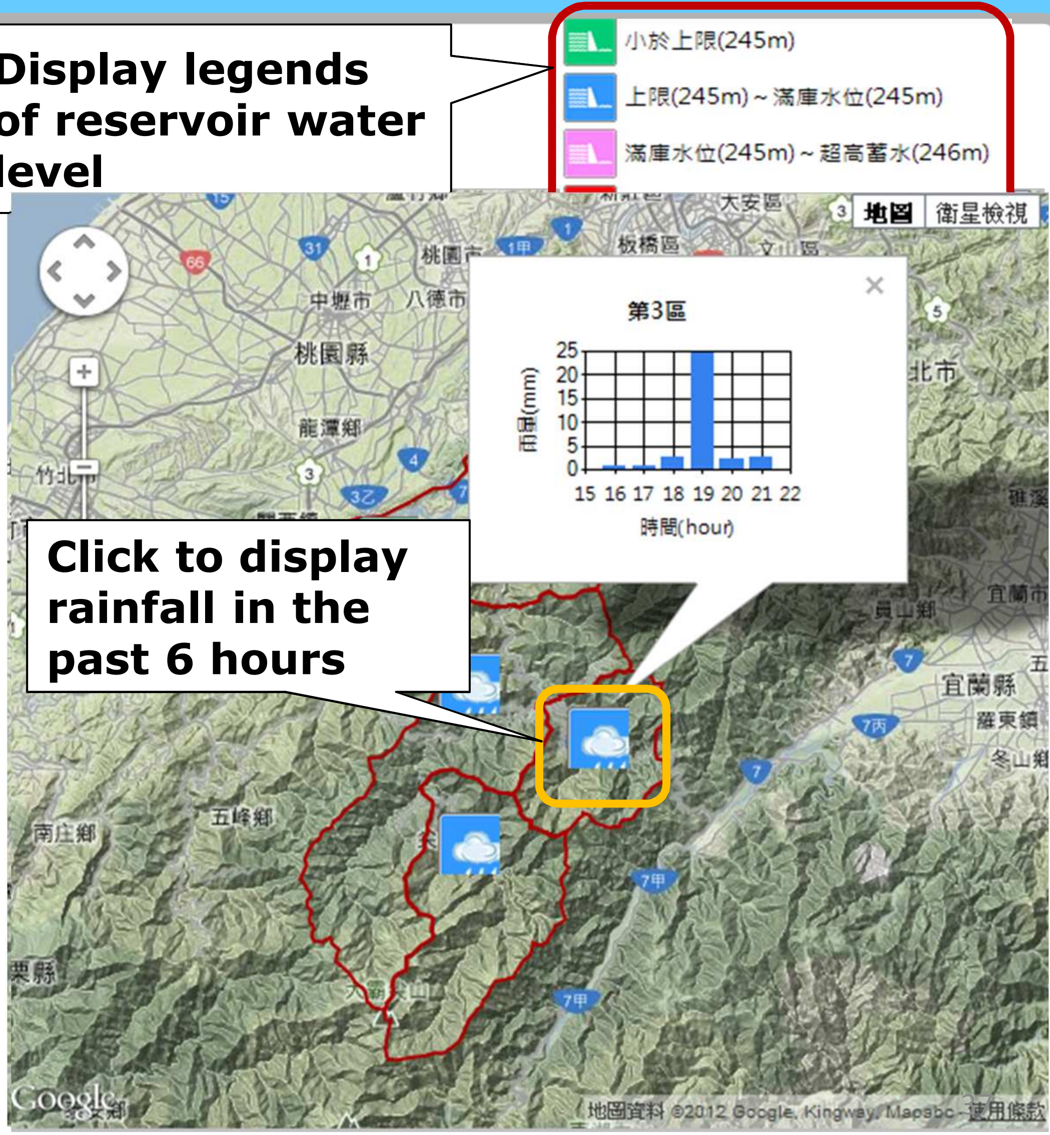
Time	Reservoir
17	243.42
18	243.37
19	243.45
20	243.31

Rainfall model:
Rainfall information (mm):

Time	I	II	III	IV
12	0.5	0	0.8	1.6
13	0.9	1.1	2.7	0

Download file: XML

Display legends of reservoir water level



Click to display rainfall in the past 6 hours

Conclusion

- With more rain-gauge inputs (in Model Q2) than four sub-catchment average inputs (in Model Q3) did not reduce the forecasting error.
- The superior contribution arising from aggregated spatial-temporal radar rainfall on inflow forecasting is particular clear at t+4~t+5.
- The radar rainfall can increase the models’ performance and reduce the time shift problem.
- The on-line early warning system built in this study can be very useful for flood control and management.

http://www.youtube.com/watch?v=jfer6mKoORo

Thanks for Your Attention