Development of Novel Artificial Neural Networks for Regional Flood Inundation Forecasts

Fi-John Chang

Distinguished Professor
National Taiwan University
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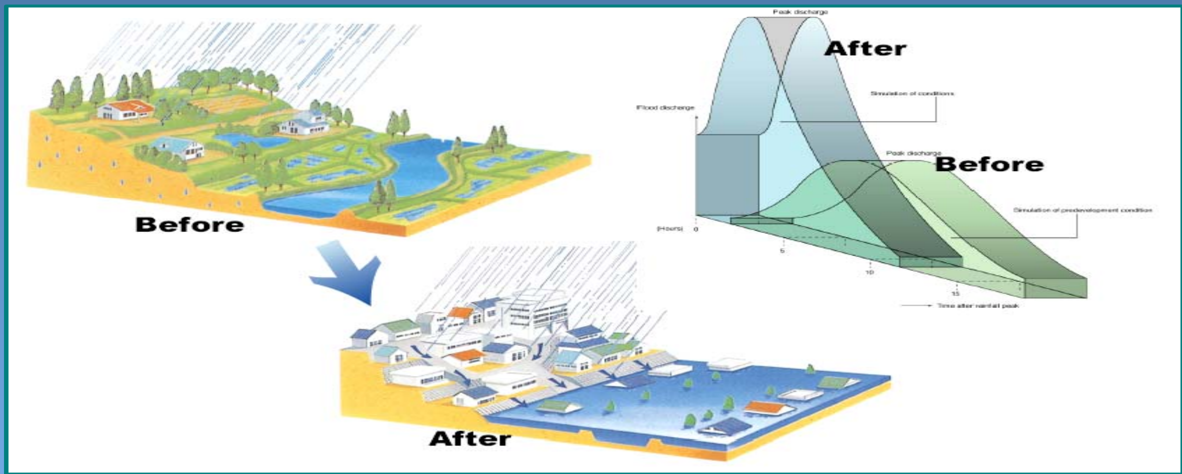
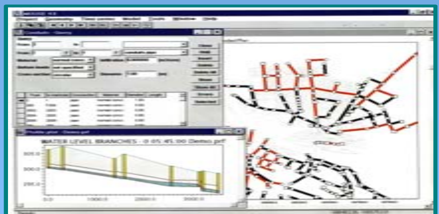
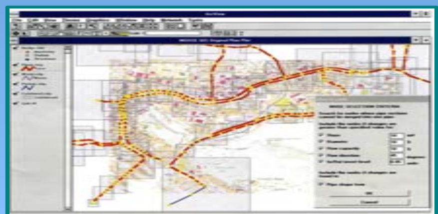
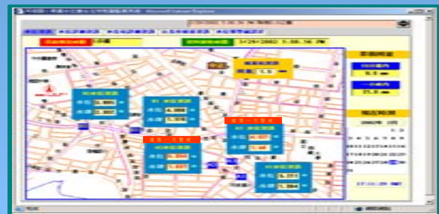
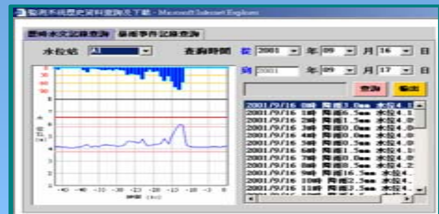
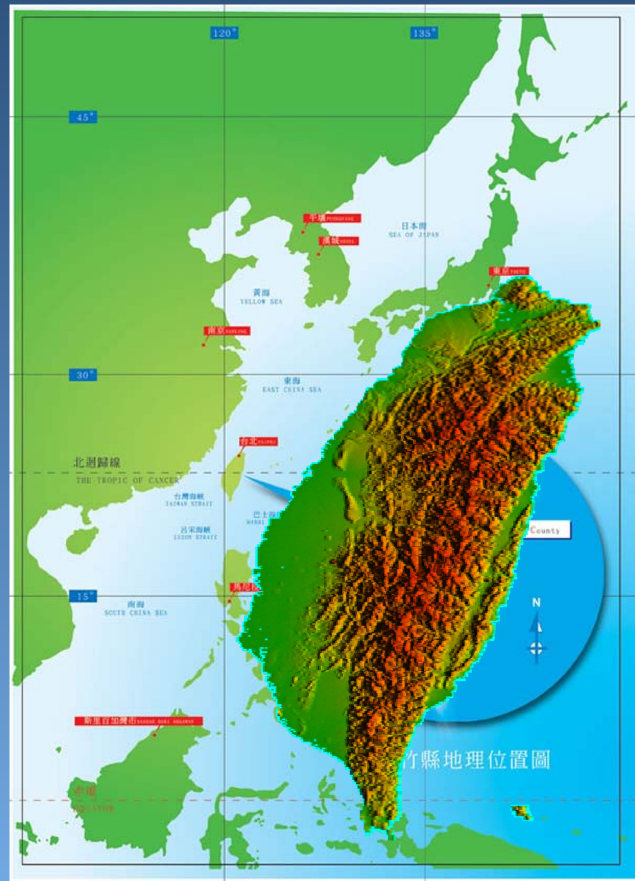




Taiwan

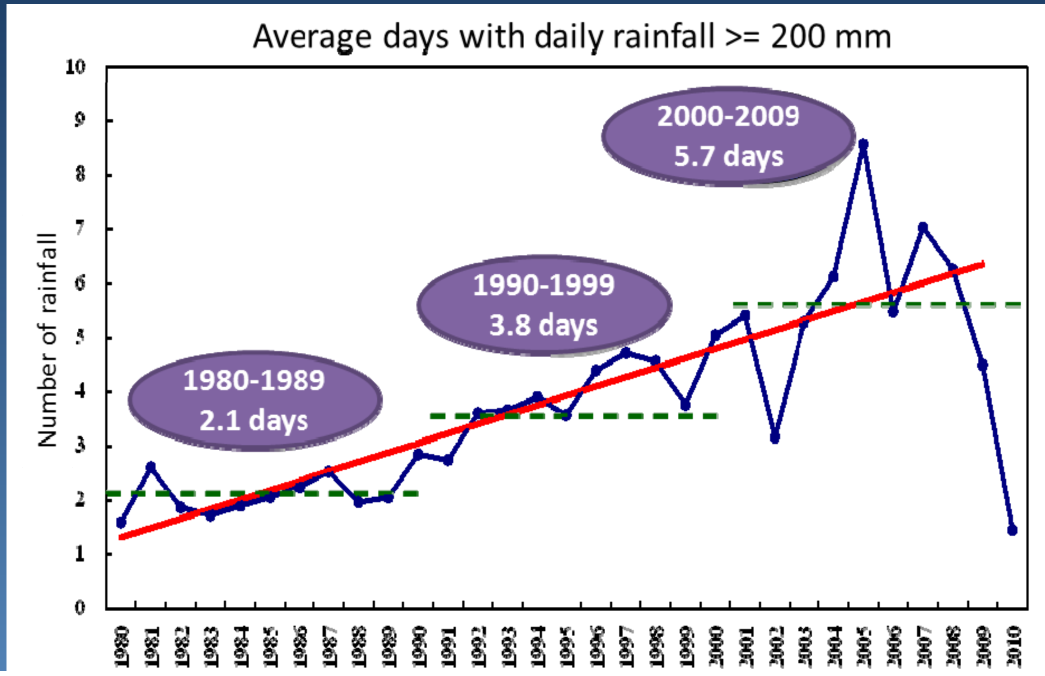
- Rainfall Distribution
  - **Annual rainfall: 2,500 mm**
  - **2.5 times the world average**
- Runoff Distribution
  - **Rivers: short and steep**
- Typhoons and Storms
  - Last century: about 350 typhoons

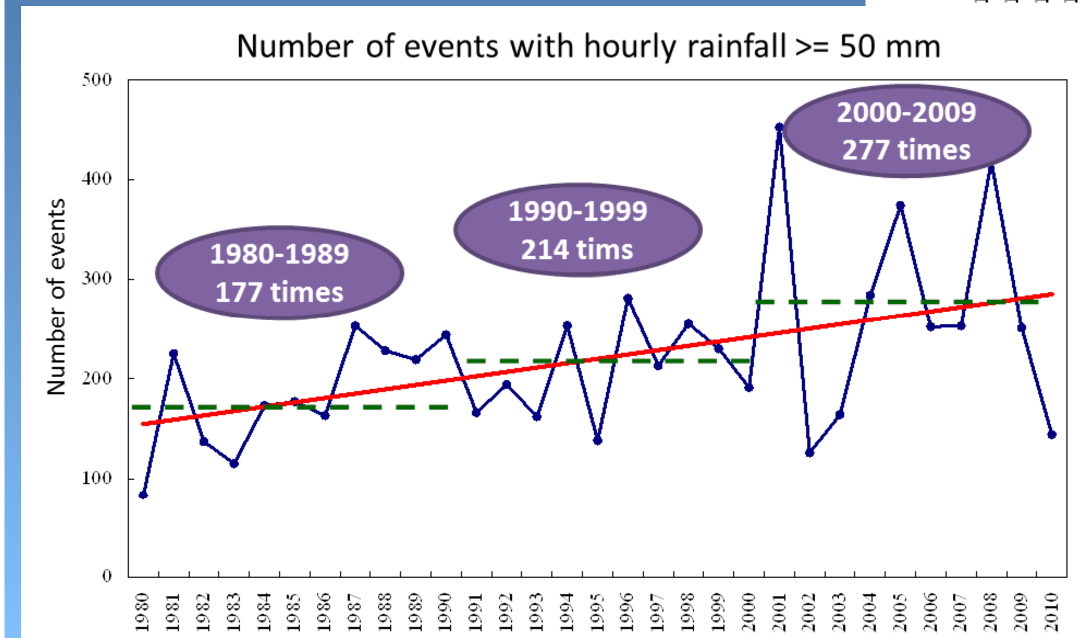


Area: 36000 km^2; Population: 24 M

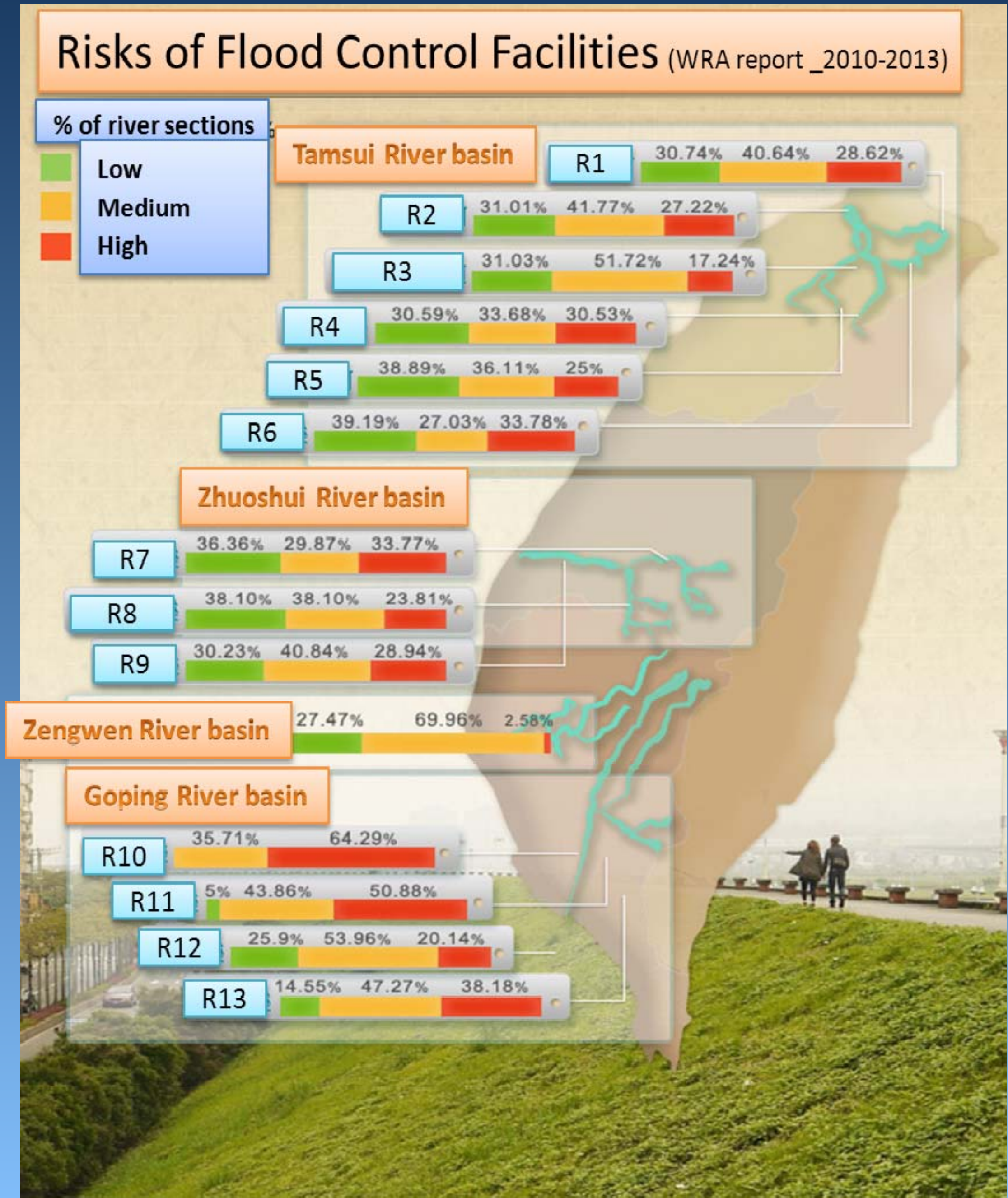
In the past 30 years

- Number of torrential rain increases
- Rainfall intensity enlarges





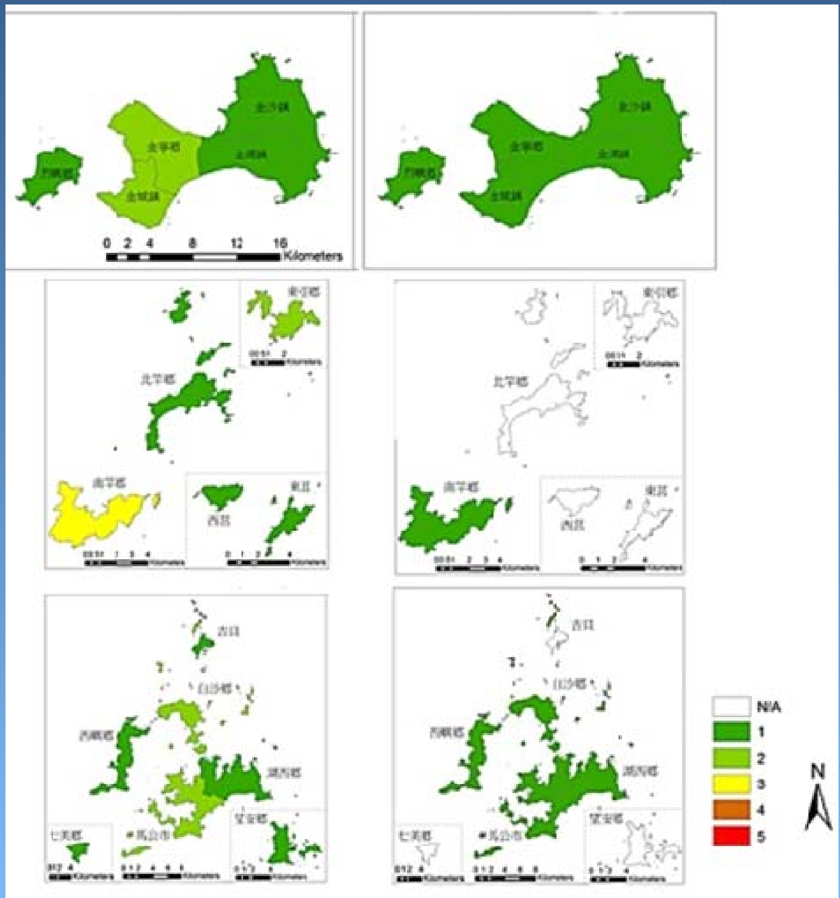
- **Risks of Flood Control Facilities**
  - Highest
    - Goping River basin
  - Lower
    - Tamsui River basin
    - Zhuoshui River basin
    - Zengwen River basin

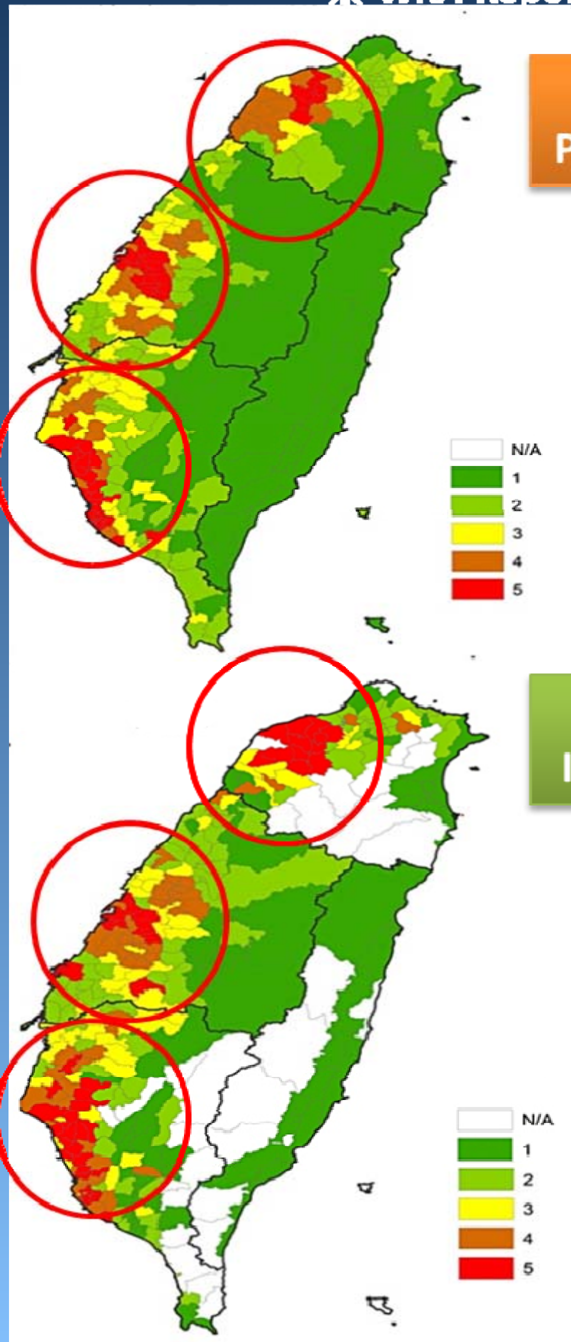


※ WRA Report_2010-2013

Risks of Water Shortage

Public **Industrial**





Risk of Public Use

Risk of Industrial Use

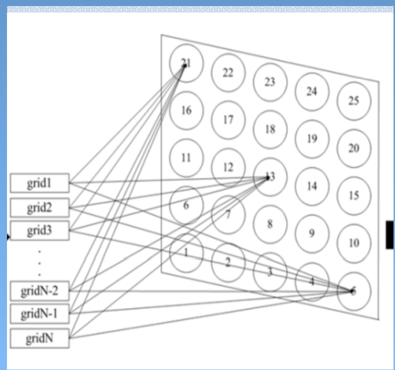
Outline

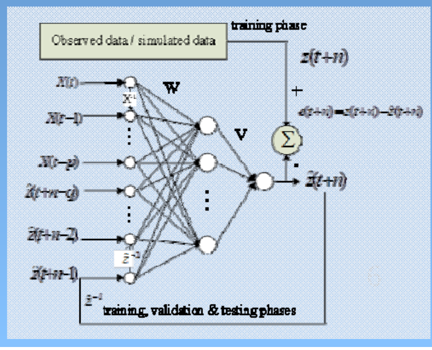
- Propose a novel methodology for nowcasting regional flood inundation maps during typhoon events

- Idea
  - ✓ form a topology of inundation maps
  - ✓ continuously update the selected map according to a forecasted total inundated volume

Methodology

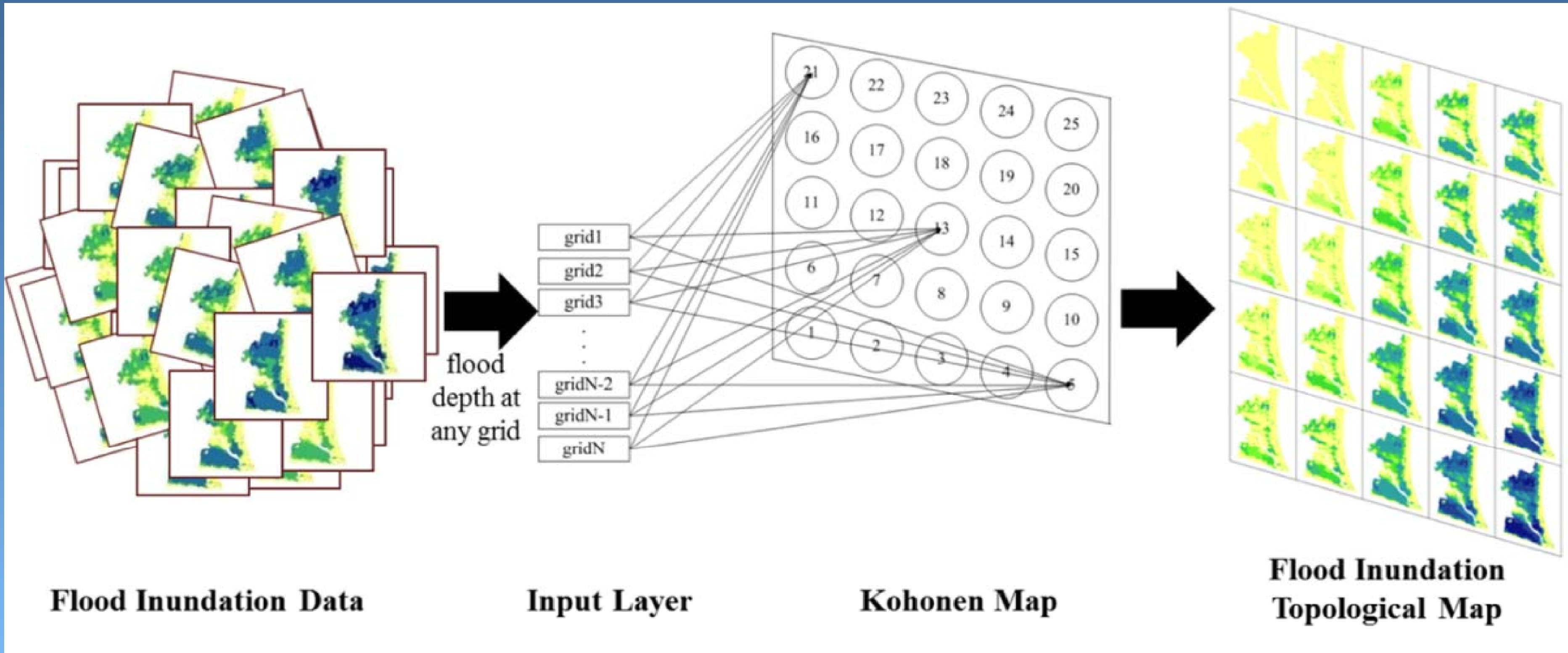
- SOM: categorize regional inundation maps into a meaningful topology
- Dynamic neural network (NARX): forecast the total inundated volume
- Weight adjusting
  - adjust the weights of selected neurons in SOM based on the forecasted total inundated volume to obtain a real-time adapted regional inundation map





Methods (SOM)

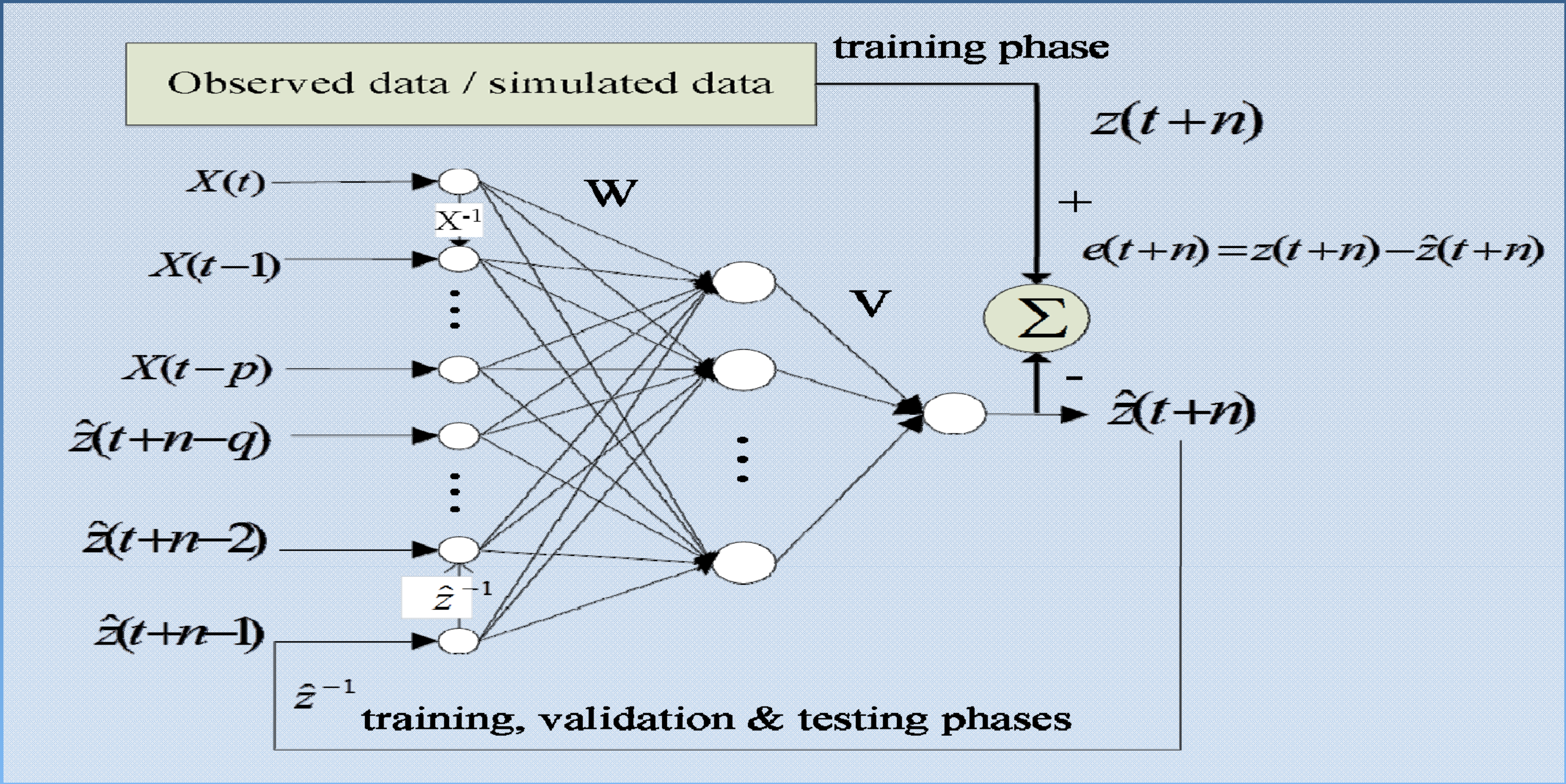
Configure the SOM to categorize a number of regional inundation maps into a meaningful topology



SOM

Methods (R-NARX)

Build a dynamic neural network (R-NARX) to forecast the total inundated volume

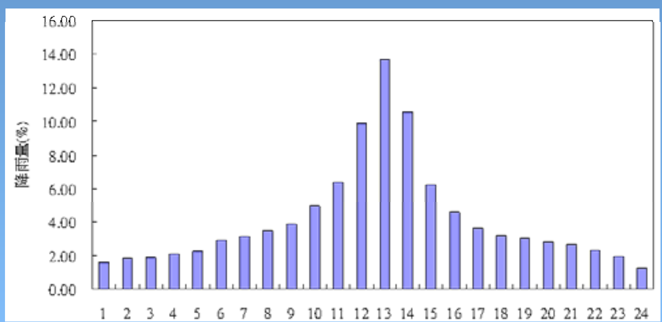


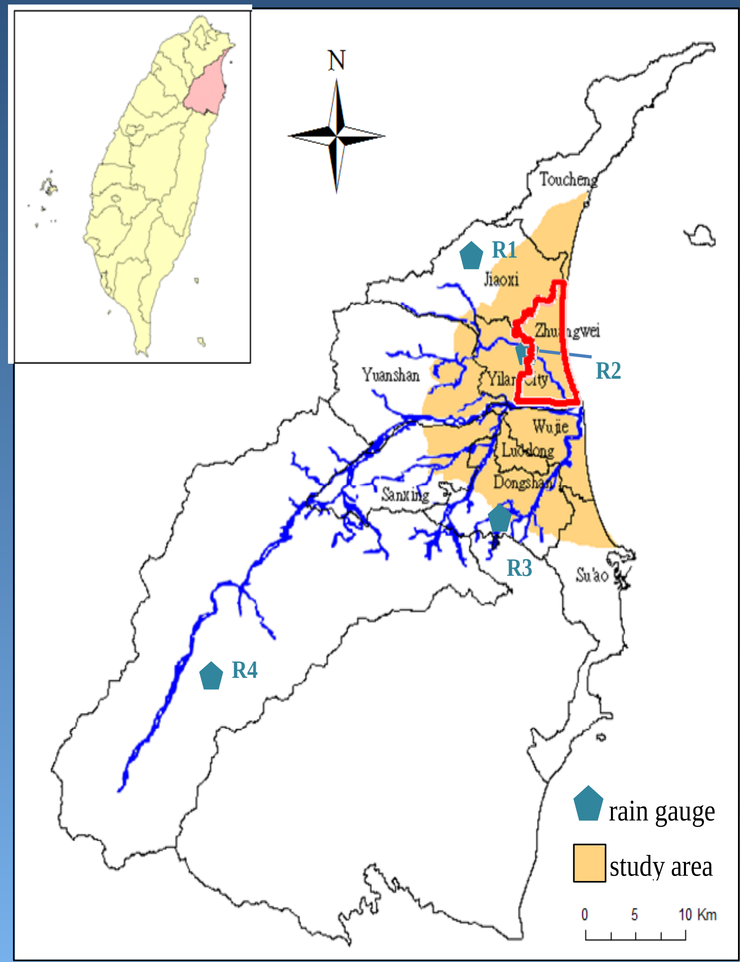
R-NARX

Study Area

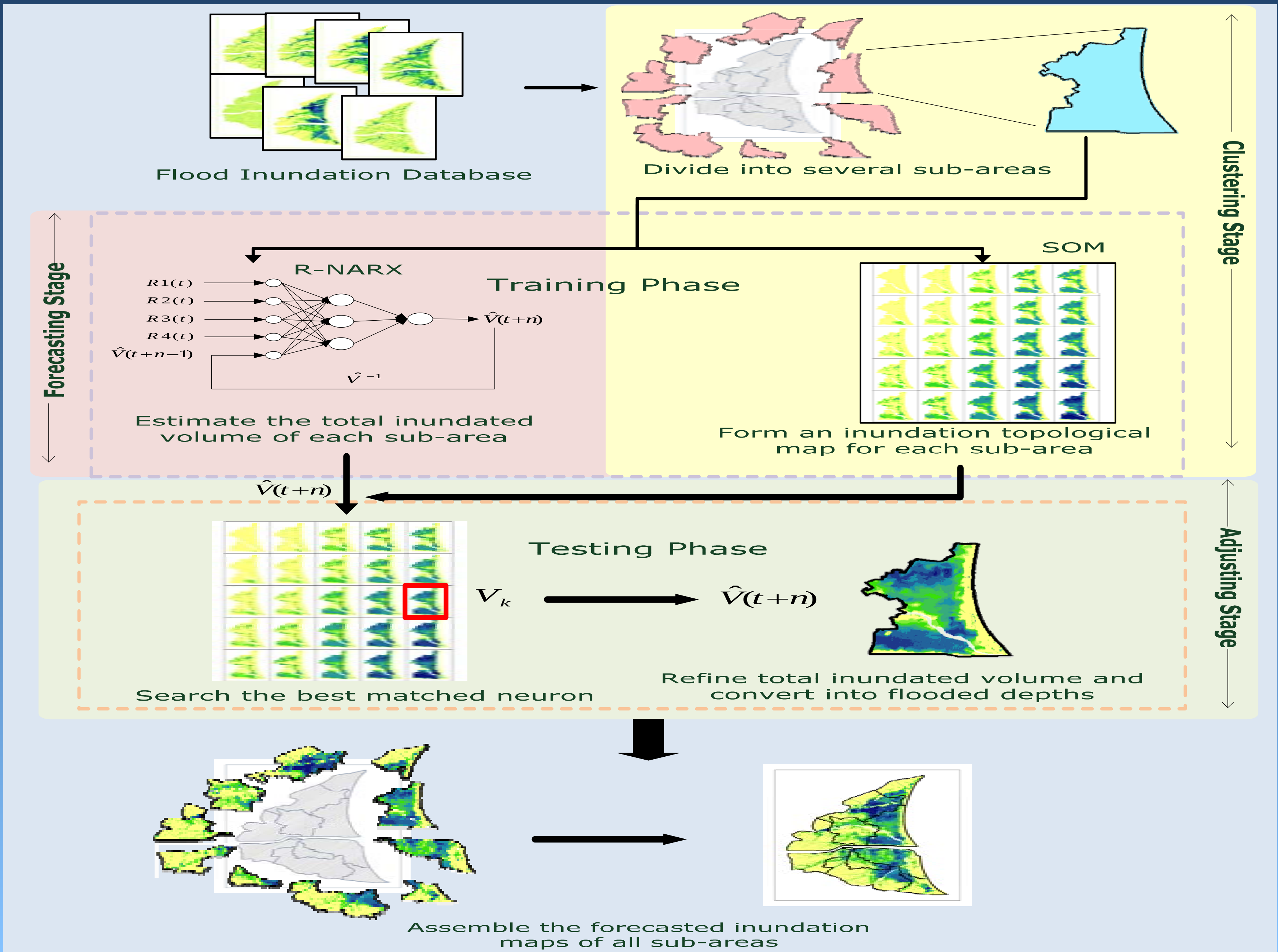
- Yilan County, Taiwan
- inundation-prone region (270 km^2)
- a total of 168,986 grids with a grid resolution of 40m x 40m (168,986 grids ≅ 270 km^2/(40m x 40m)

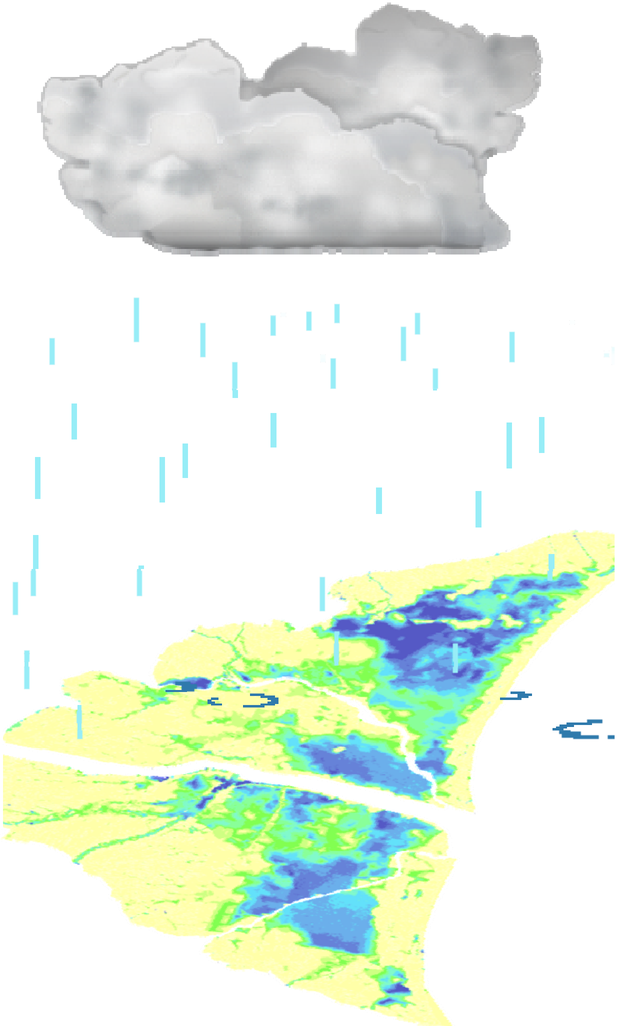
- Data
  - 31 historical rainfall events
  - 24 designed rainfall events **with various return periods**





Model Construction



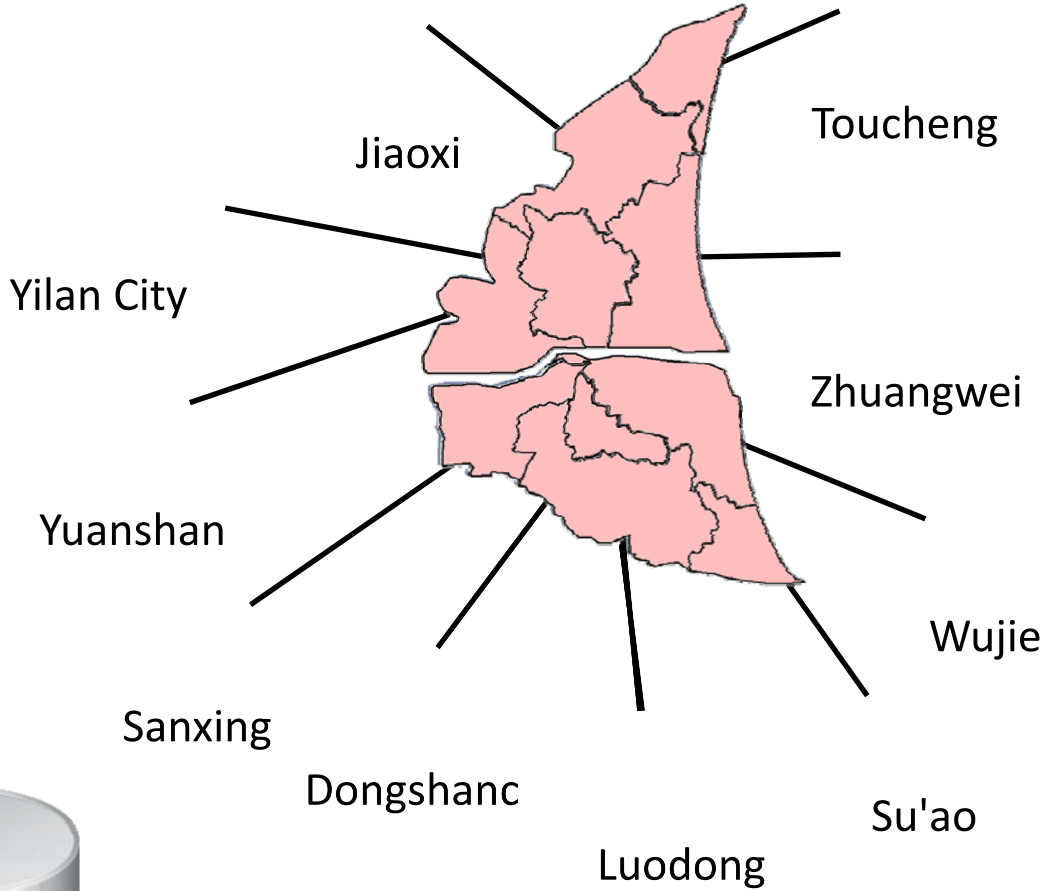


Regional flood inundation maps.

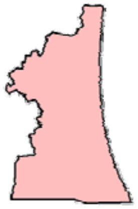
Flood Inundation Database.

The total number of data in this study is huge
(55 events × 24 hours × 168,986 grids= 223,061,520).

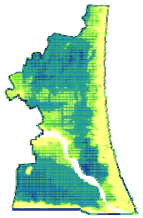
The investigated area focus on the inundation-prone region, which is about 270 km^2 and is divided into a total of 168,986 grids with a grid resolution of 40m $\times$ 40m.

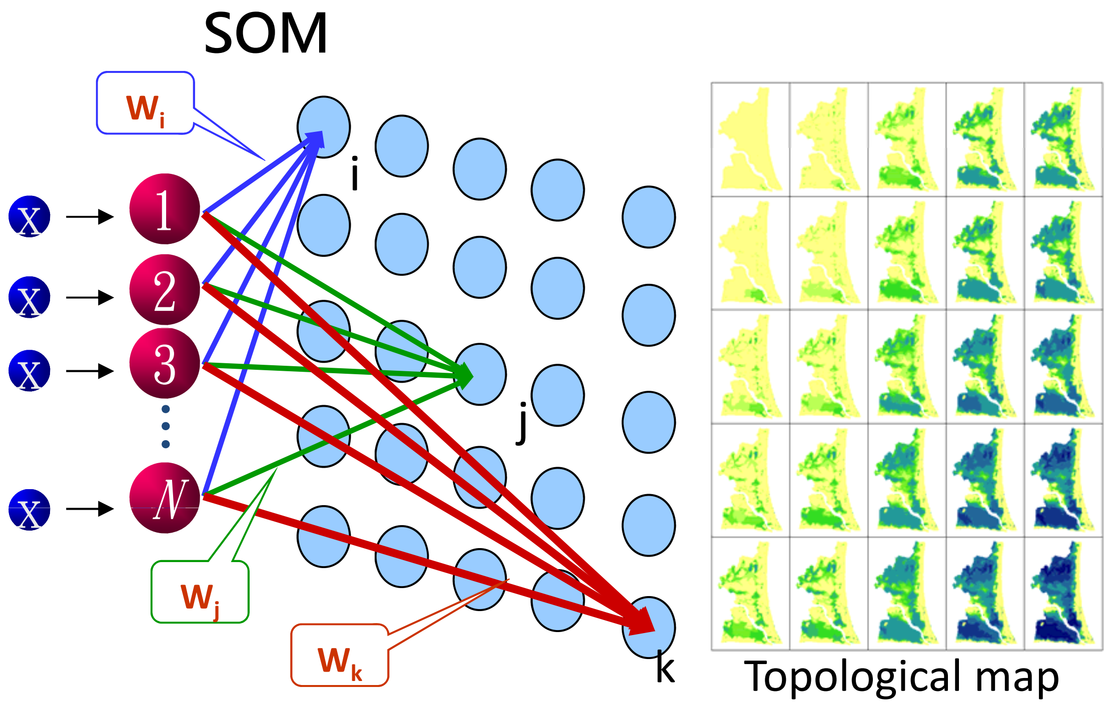


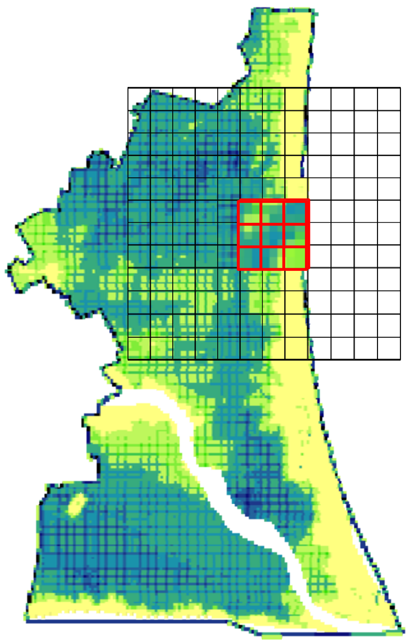
The whole area is divided into ten sub-areas.

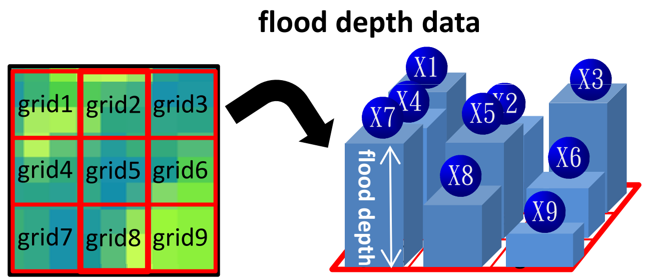


Form an inundation topological map for each sub-area.

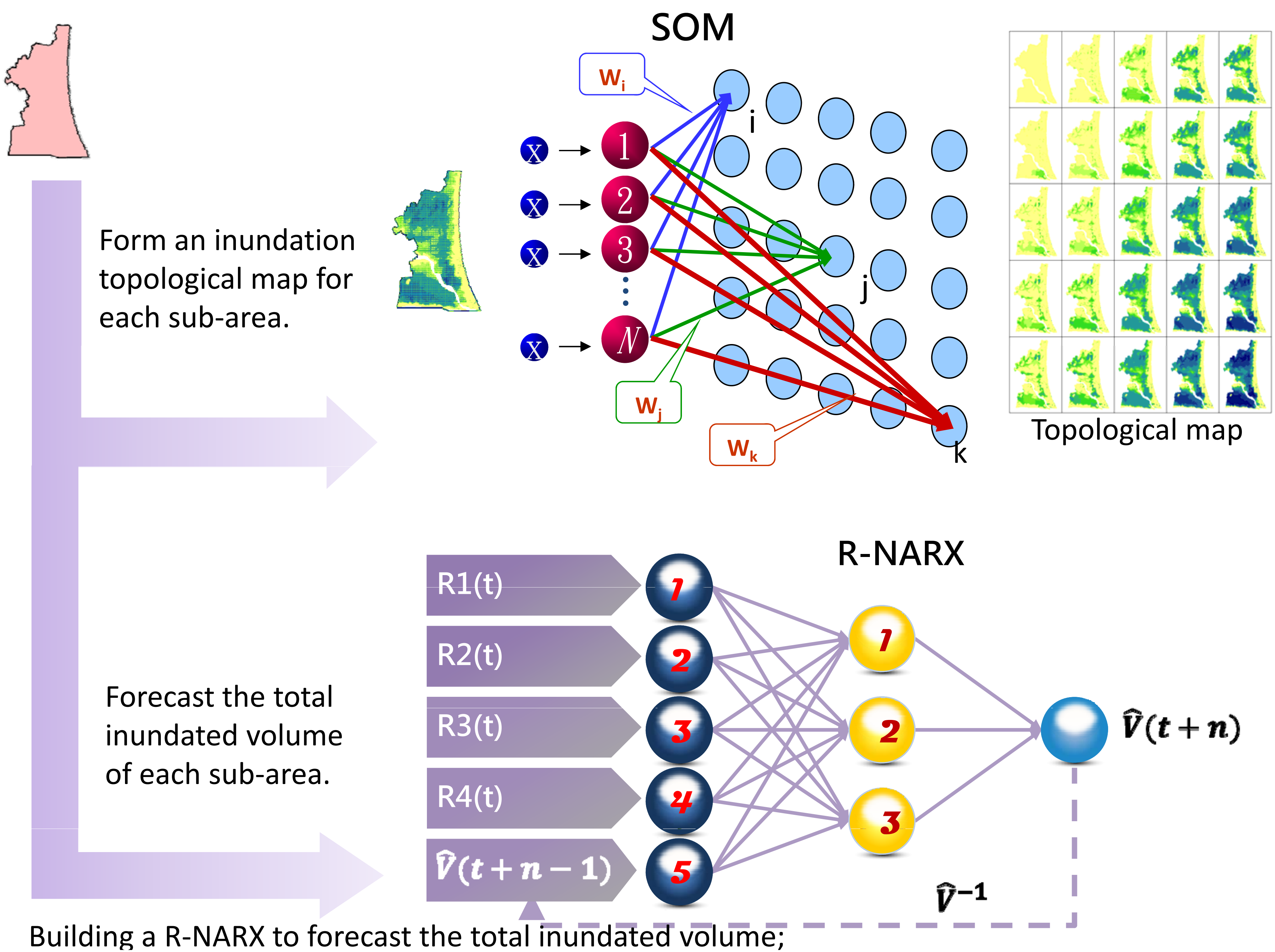


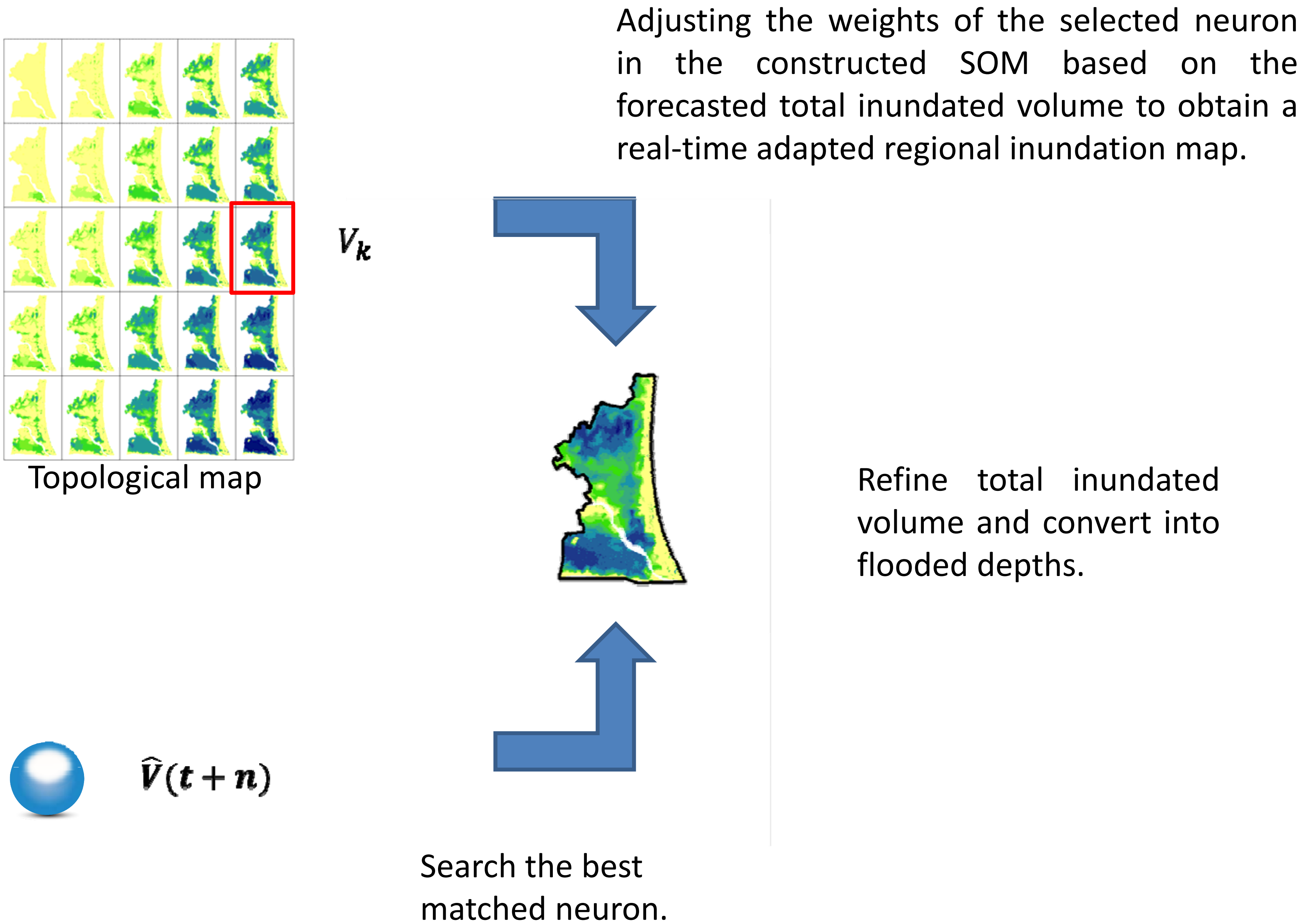






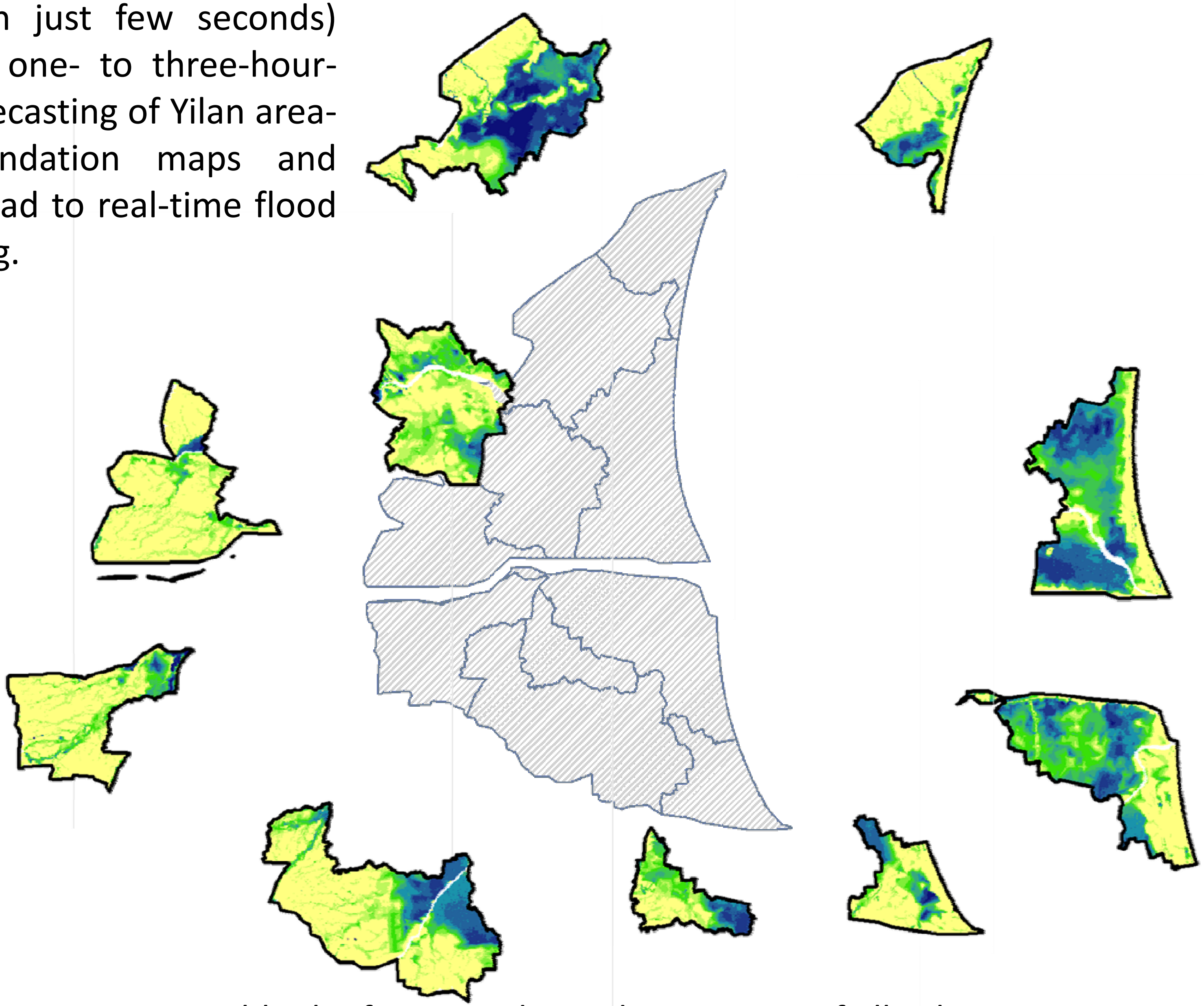
Configuring the SOM to categorize a large number of regional inundation maps into a meaningful topology;


SOM
w_i
i
j
k
w_j
w_k
x
1
2
3
N
Topological map
Form an inundation topological map for each sub-area.
R-NARX
R1(t)
R2(t)
R3(t)
R4(t)
$\hat{V}(t+n-1)$
1
2
3
4
5
1
2
3
$\hat{V}(t+n)$
$\hat{V}^{-1}$
Forecast the total inundated volume of each sub-area.
Building a R-NARX to forecast the total inundated volume;



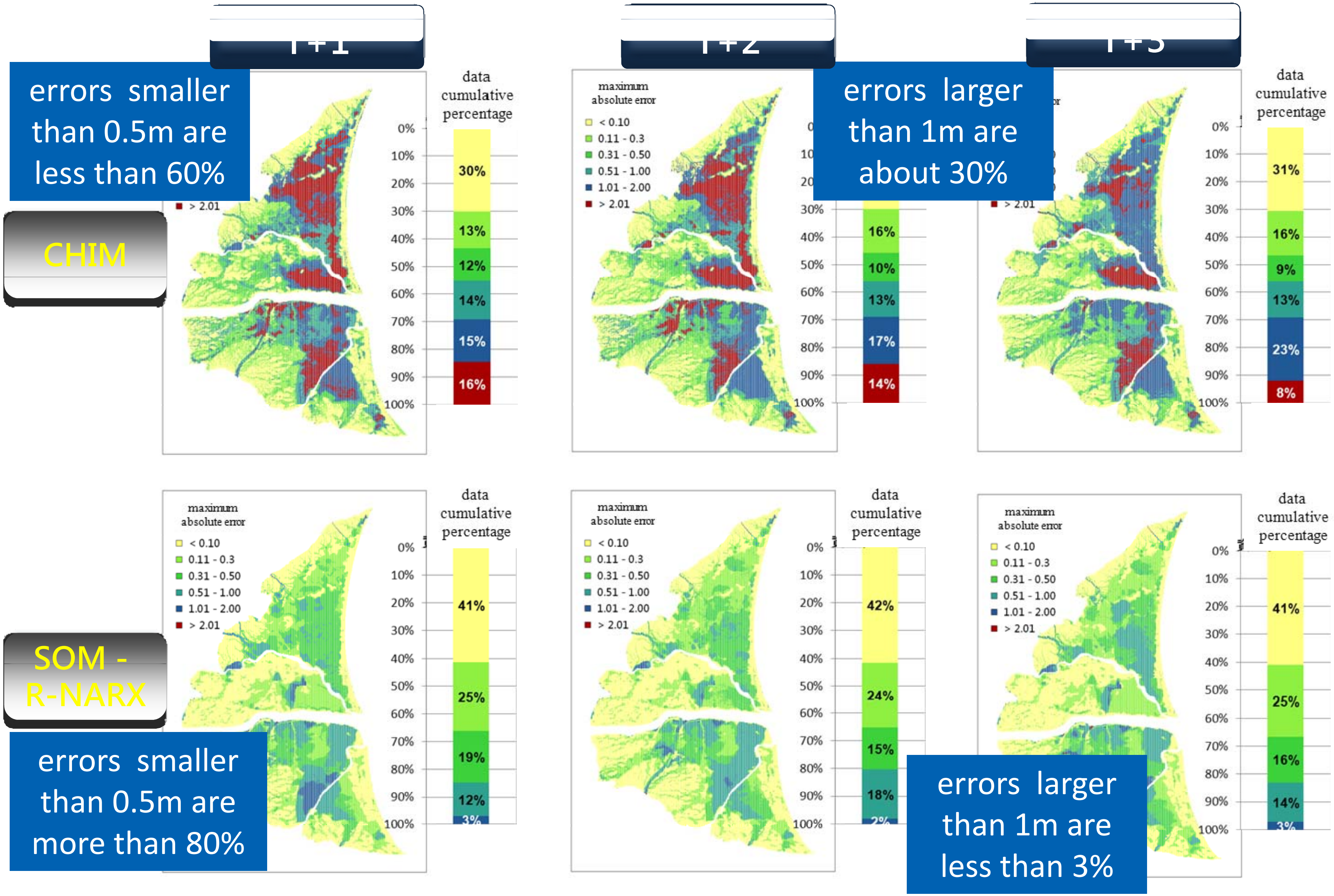
Adjusting the weights of the selected neuron in the constructed SOM based on the forecasted total inundated volume to obtain a real-time adapted regional inundation map.
V_k
Topological map
Refine total inundated volume and convert into flooded depths.
$\hat{V}(t+n)$
Search the best matched neuron.

SOM - R-NARX can very quickly (in just few seconds) carry out one- to three-hour-ahead forecasting of Yilan area-wide inundation maps and thereby lead to real-time flood forecasting.



Assemble the forecasted inundation maps of all sub-areas.

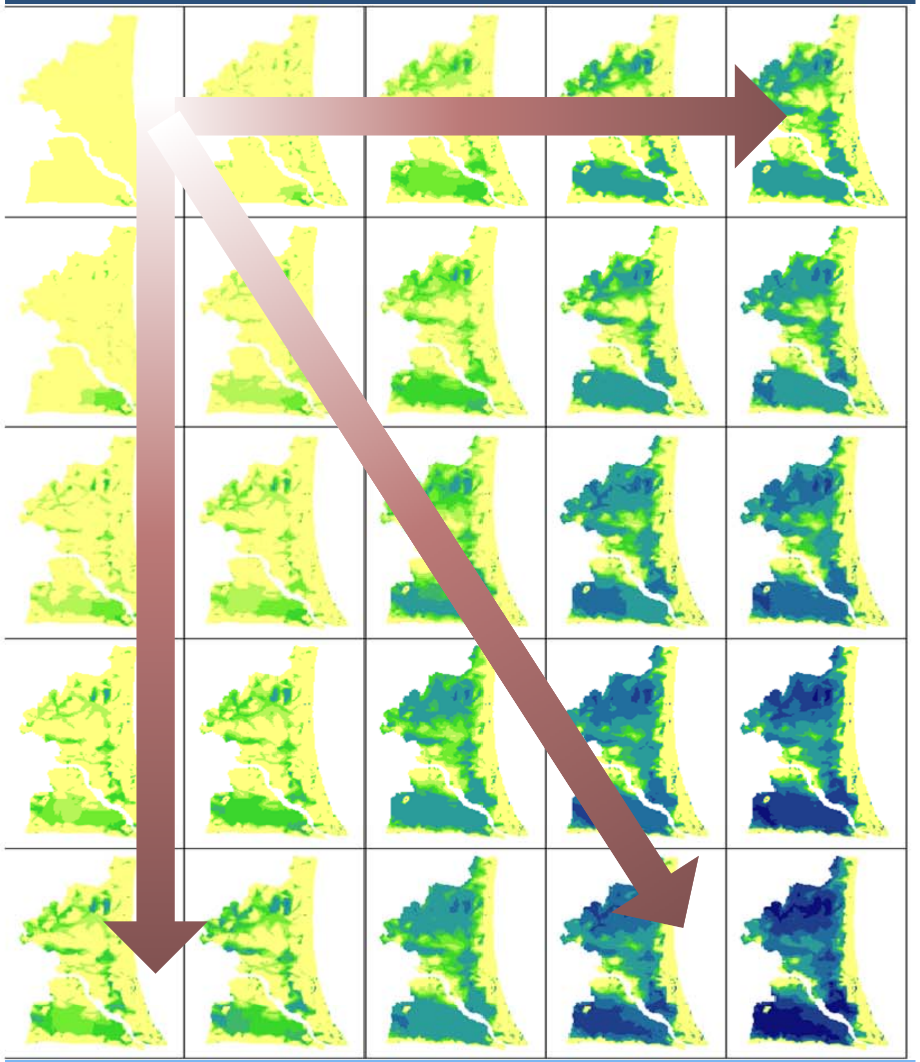
The maximum absolute errors



Results

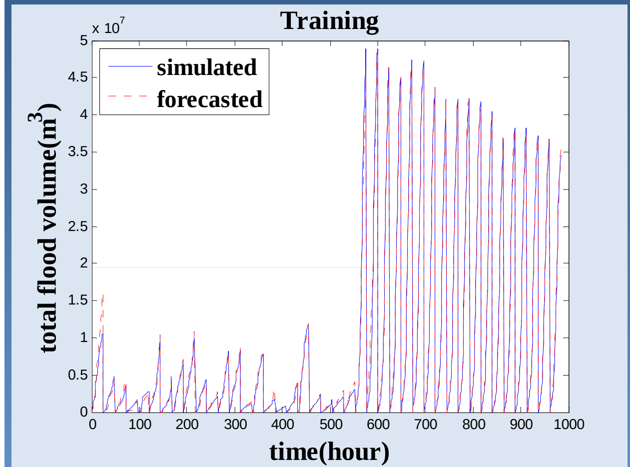
Weight information of the 5×5 neurons in the SOM for Zhuangwei

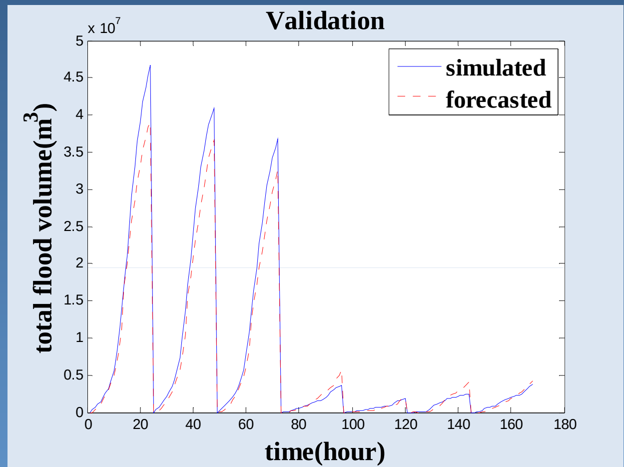
Item	Weight (5 × 5 neurons)				
Maximum inundation depths (m)	0.35	0.53	0.68	1.49	1.80
	0.50	0.47	0.77	1.59	1.91
	0.67	0.67	1.02	1.86	2.00
	1.21	1.10	1.33	2.05	2.37
	1.44	1.48	1.52	2.22	2.69
Mean inundation depths (m)	0.01	0.04	0.11	0.22	0.30
	0.03	0.05	0.14	0.31	0.42
	0.05	0.08	0.23	0.52	0.65
	0.08	0.14	0.36	0.72	0.92
	0.12	0.17	0.45	0.82	1.17
Total inundated volume ($10^6 m^3$)	0.25	1.25	3.79	7.51	10.44
	0.87	1.79	4.96	10.61	14.47
	1.89	2.92	8.00	17.69	22.27
	2.88	4.78	12.42	24.83	31.60
	4.03	5.93	15.36	28.18	40.36

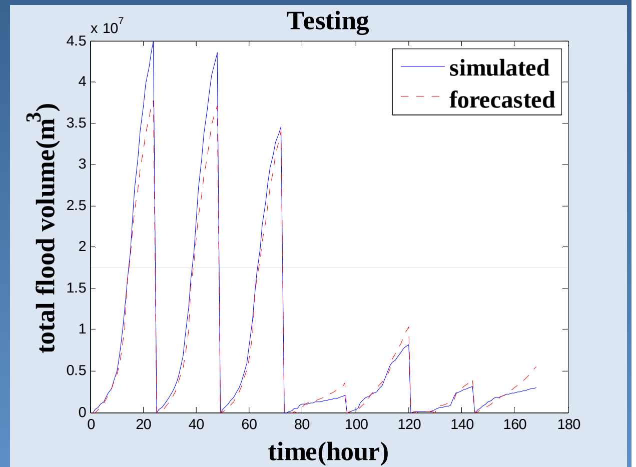


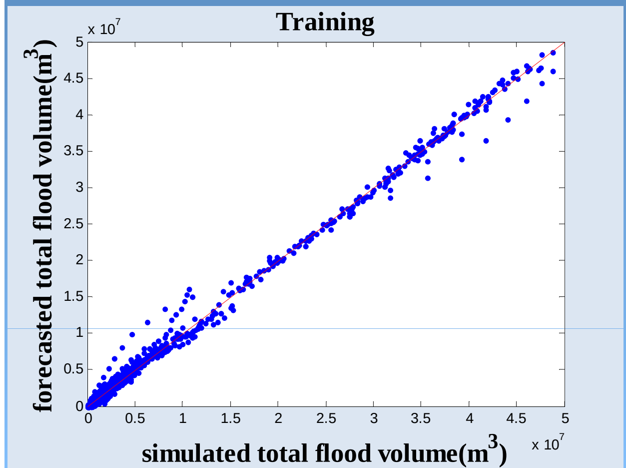
Results

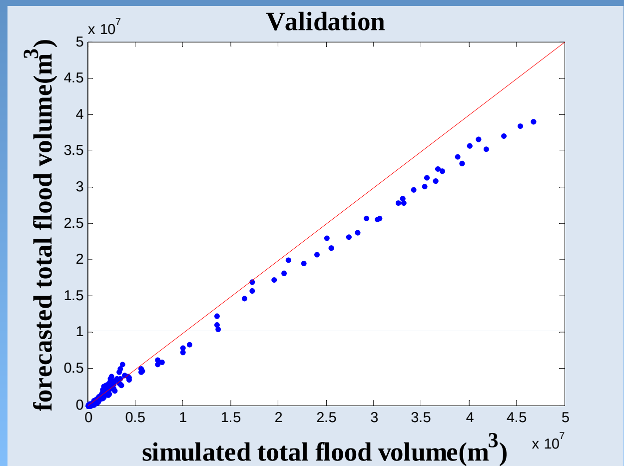
Simulated and one-hour-ahead forecasted total flood volumes in Zhuangwei (the 6th sub-area)

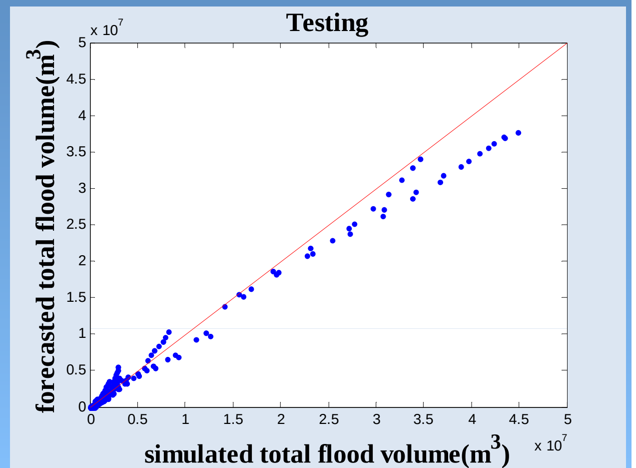






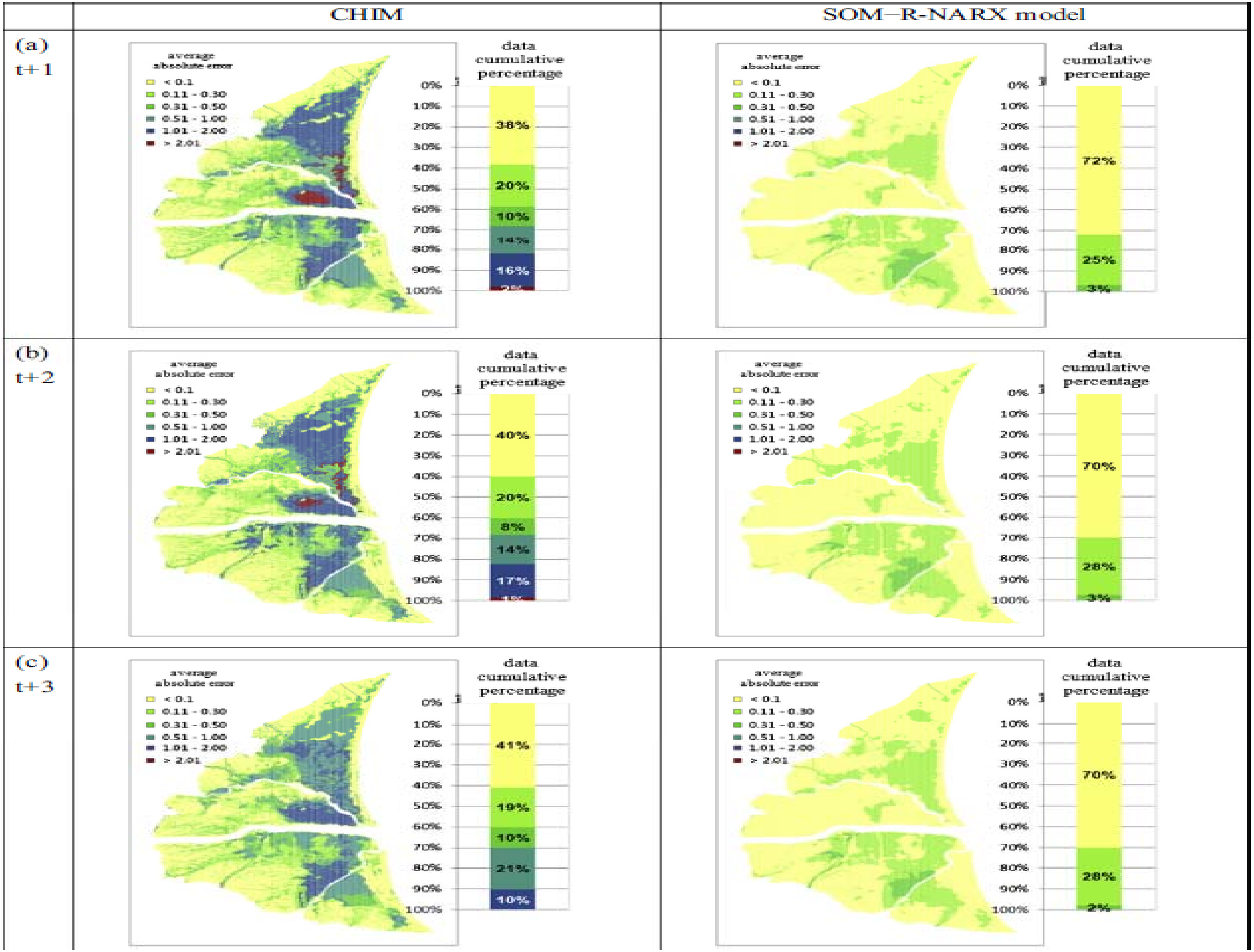




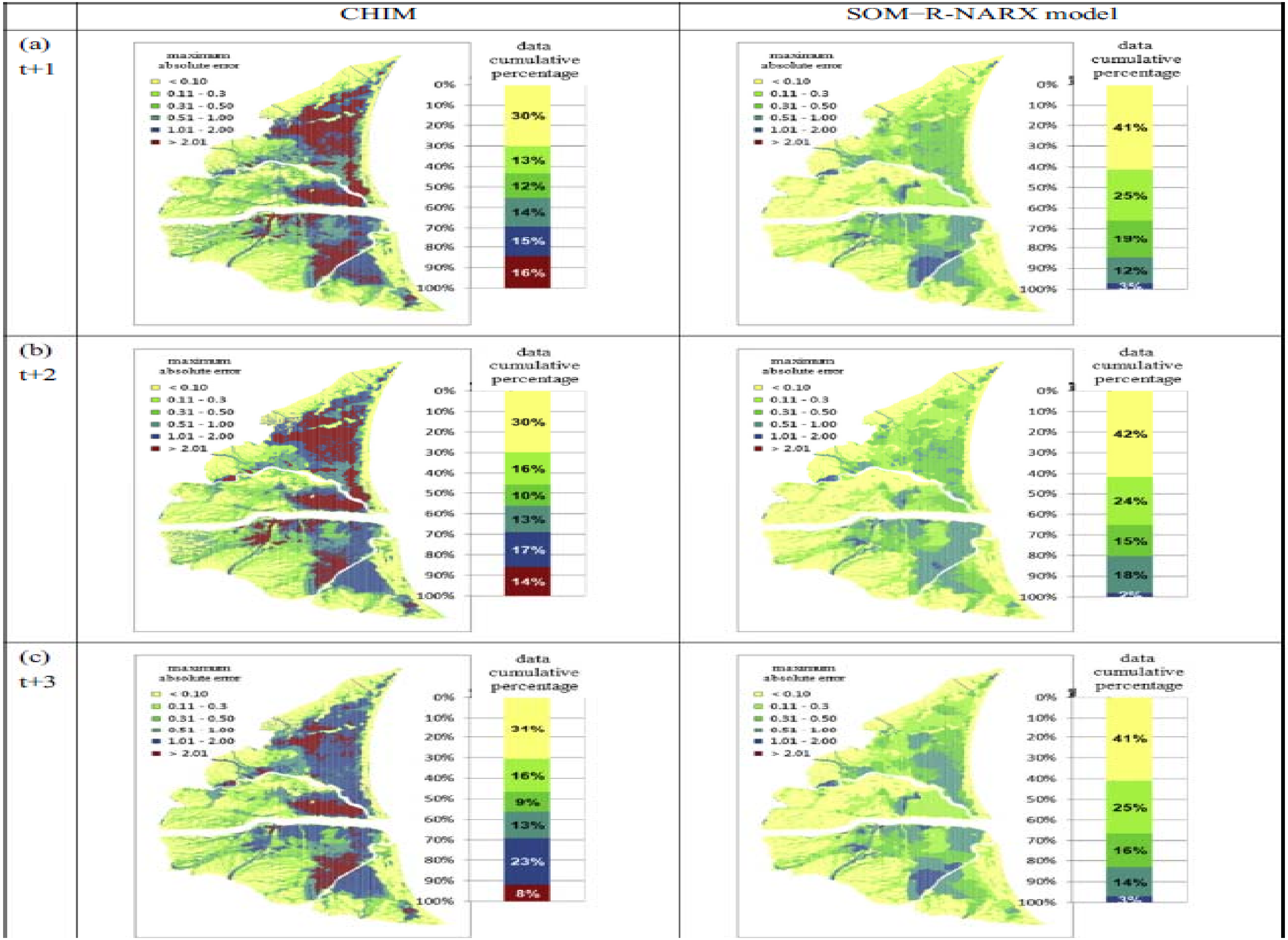


Performance of 1- to 3-h-ahead forecasts of inundation depths at each sub-areas by the SOM-R-NARX models.

Sub-area	Time step	RMSE (m)			R^2		
		Training	Validation	Testing	Training	Validation	Testing
1	$t+1$	0.10	0.11	0.12	0.93	0.90	0.89
	$t+2$	0.10	0.11	0.11	0.93	0.91	0.90
	$t+3$	0.11	0.11	0.11	0.91	0.91	0.91
2	$t+1$	0.13	0.17	0.16	0.92	0.91	0.90
	$t+2$	0.13	0.16	0.17	0.92	0.92	0.89
	$t+3$	0.14	0.16	0.15	0.92	0.91	0.91
3	$t+1$	0.10	0.10	0.10	0.97	0.97	0.97
	$t+2$	0.10	0.11	0.11	0.97	0.97	0.96
	$t+3$	0.10	0.12	0.12	0.96	0.97	0.96
4	$t+1$	0.09	0.07	0.10	0.96	0.98	0.96
	$t+2$	0.10	0.08	0.10	0.96	0.98	0.95
	$t+3$	0.10	0.08	0.11	0.96	0.97	0.95
5	$t+1$	0.09	0.08	0.09	0.98	0.98	0.98
	$t+2$	0.10	0.09	0.11	0.98	0.98	0.97
	$t+3$	0.10	0.10	0.11	0.97	0.97	0.97
6	$t+1$	0.08	0.10	0.10	0.98	0.98	0.97
	$t+2$	0.08	0.12	0.12	0.98	0.98	0.96
	$t+3$	0.08	0.11	0.11	0.97	0.98	0.96
7	$t+1$	0.08	0.08	0.08	0.92	0.92	0.91
	$t+2$	0.08	0.08	0.08	0.92	0.92	0.91
	$t+3$	0.08	0.08	0.09	0.92	0.92	0.90
8	$t+1$	0.15	0.19	0.18	0.91	0.92	0.89
	$t+2$	0.15	0.18	0.17	0.91	0.92	0.90
	$t+3$	0.15	0.19	0.19	0.91	0.91	0.89
9	$t+1$	0.11	0.15	0.16	0.96	0.94	0.93
	$t+2$	0.12	0.14	0.17	0.96	0.95	0.93
	$t+3$	0.12	0.14	0.17	0.95	0.95	0.93
10	$t+1$	0.11	0.11	0.11	0.95	0.95	0.94
	$t+2$	0.11	0.12	0.12	0.95	0.95	0.93
	$t+3$	0.11	0.12	0.13	0.94	0.95	0.93



Distribution of the average absolute errors with respect to the CHIM and the SOM–R-NARX model during the Design-A event.



Distribution of the maximum absolute errors with respect to the CHIM and the SOM–R-NARX model during the Design-A event.

Results

Comparison of model execution efficiency between the CHIM and the SOM–R-NARX model

Item	CHIM	SOM–R-NARX model
Total number of sub-models	318	50
Parameter storage memory size	662 KB	78322 KB
Time-consumption of hourly forecasting	2.0 seconds	2.1 seconds

Conclusions

- The proposed approach offers an insightful and promising methodology for real-time forecasting 2-dimensional visible inundation maps during storm events.
- The regional inundation maps stored in the SOM can be instantly updated during storm events and the precision of the forecasted inundation maps can be significantly increased by the real-time forecasts obtained from the R-NARX network. The proposed hybrid modelling process offers a new insightful methodology in realizing multi-step-ahead real-time inundation maps based on rainfall data and historical inundation depths.
- The proposed models can very quickly (in few seconds) carry out one- to three-hour-ahead forecasting of Yilan area-wide inundation maps and thereby lead to real-time flood forecasting.

Chang, L.C., Shen, H.Y., Chang, F.J.*, 2014, "Regional flood inundation nowcast using hybrid SOM and dynamic neural networks", Journal of Hydrology, 519: 476-489.

THANK YOU FOR YOUR ATTENTION

Fi-John Chang

Department of Bioenvironmental Systems Engineering

National Taiwan University

changfj@ntu.edu.tw