3rd Workshop of the
International Precipitation Working Group
Melbourne, Australia, 23-27 October 2006

Modeling storm hydrographs in a mid-size basin using satellite rainfall estimates

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Rainfall-runoff models of any type need rainfall areal estimates as input.

Characteristics of operational rain-gauge networks:

1. Low spatial density of stations

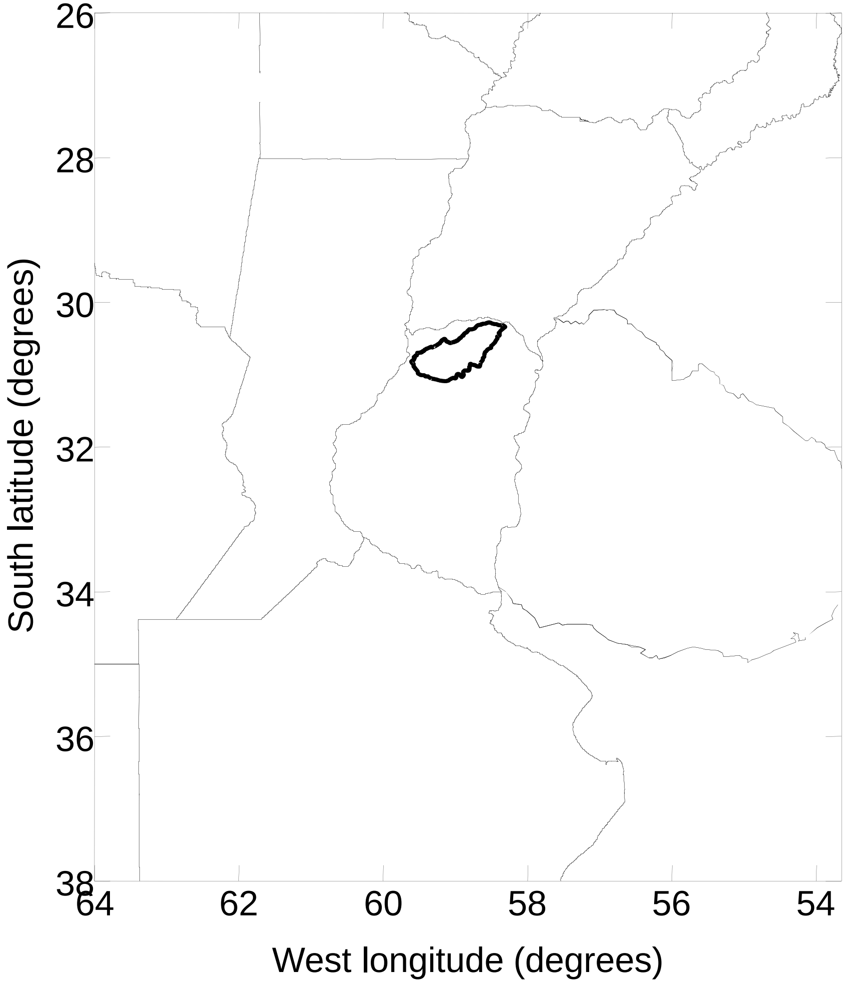
1. Irregular spatial distribution

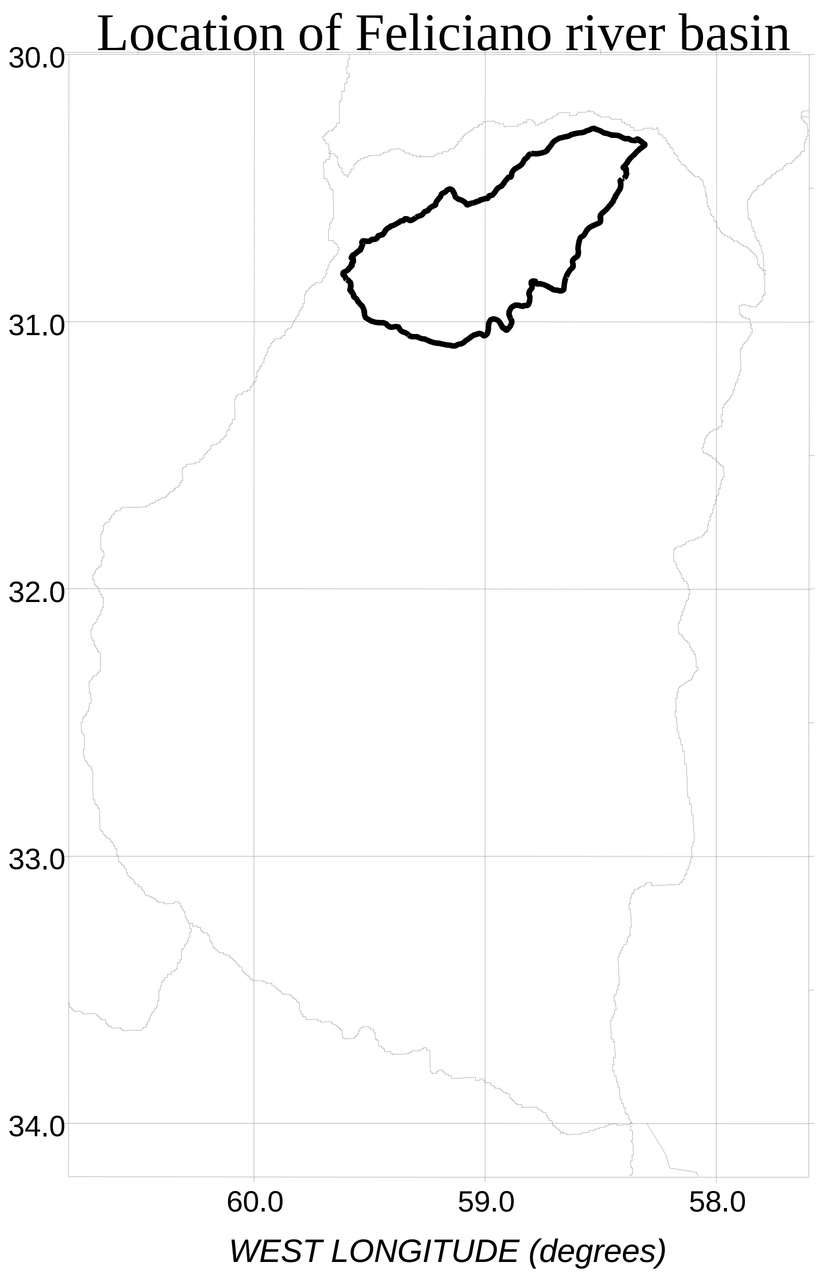
Intrinsic characteristic of rainfall:

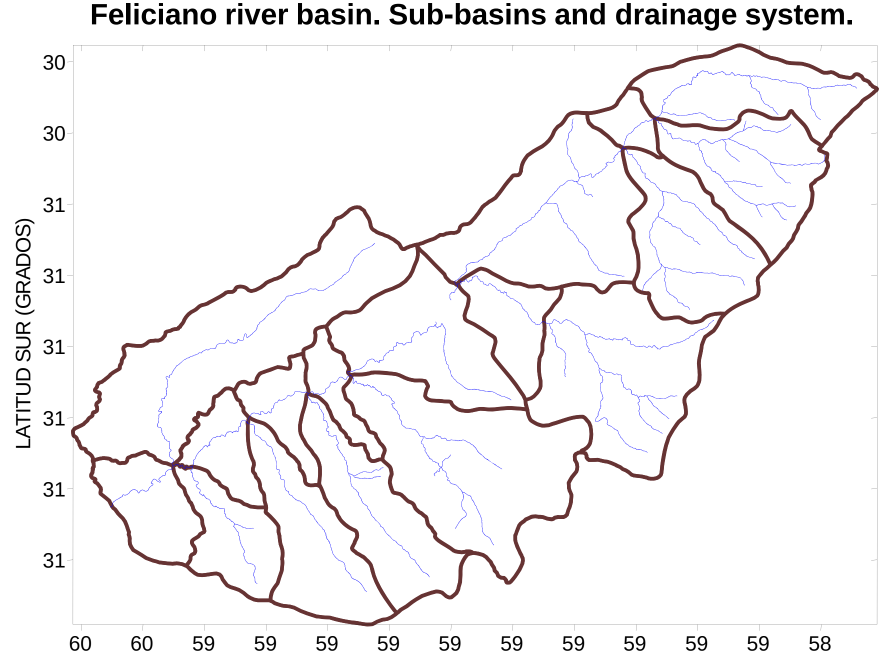
High spatial variability

Consequence: Important errors in areal rainfall estimates over sub-basins or other model input areas.

Location of the Feliciano River Basin in the Province of Entre Ríos (Argentina)

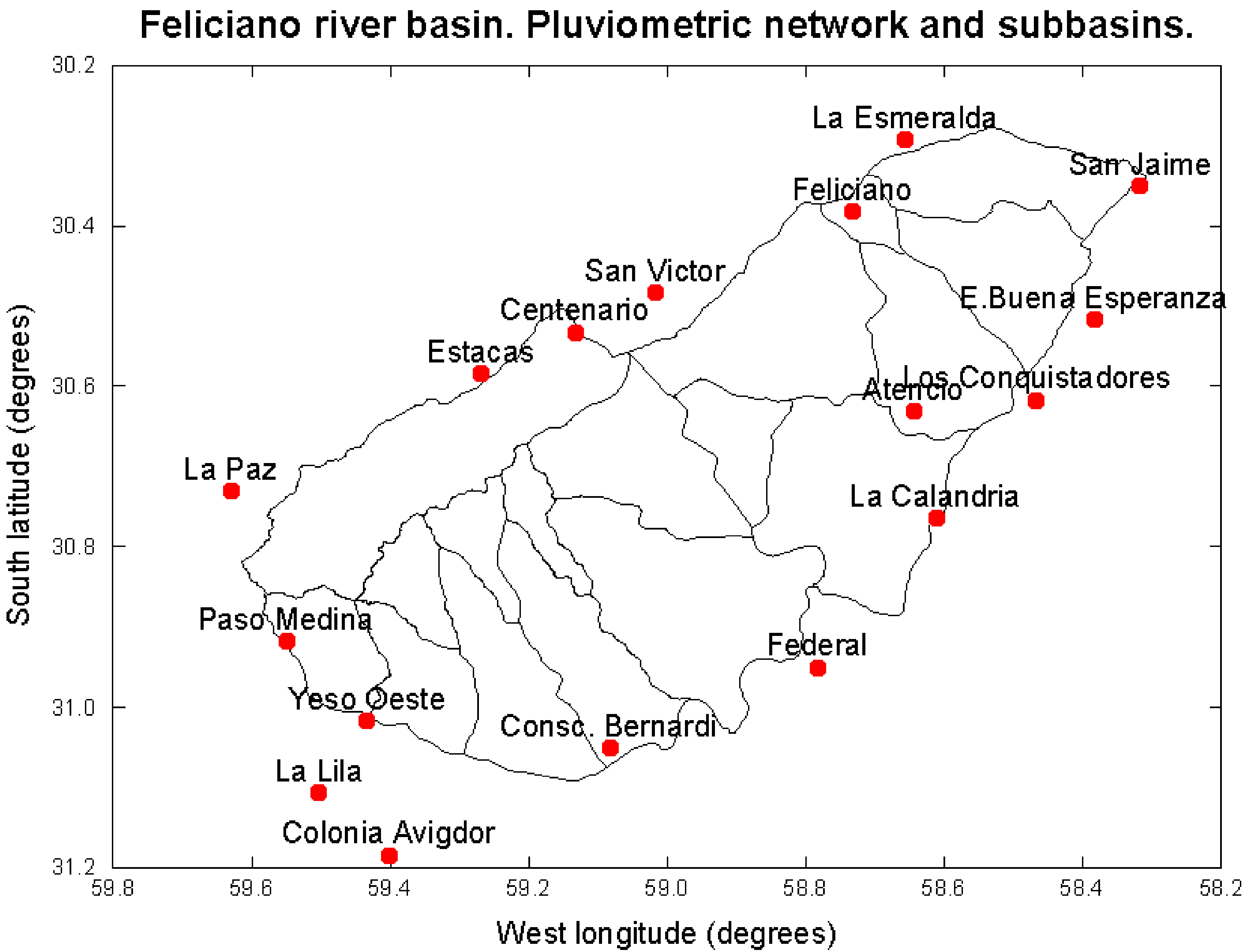






A division in 17 sub-basins and basin segments was made for hydrologic modelling purposes

Lag time for this mid-size basin (5500 km2): ~ 4-5 days


Feliciano river basin. Pluviometric network and subbasins.
South latitude (degrees)
West longitude (degrees)
30.2
30.4
30.6
30.8
31.0
31.2
59.8
59.6
59.4
59.2
59.0
58.8
58.6
58.4
58.2
La Esmeralda
San Jaime
Feliciano
San Victor
Centenario
E.Buena Esperanza
Estacas
Los Conquistadores
Atencio
La Paz
La Calandria
Paso Medina
Federal
Yeso Oeste
Consc. Bernardi
La Lila
Colonia Avigdor

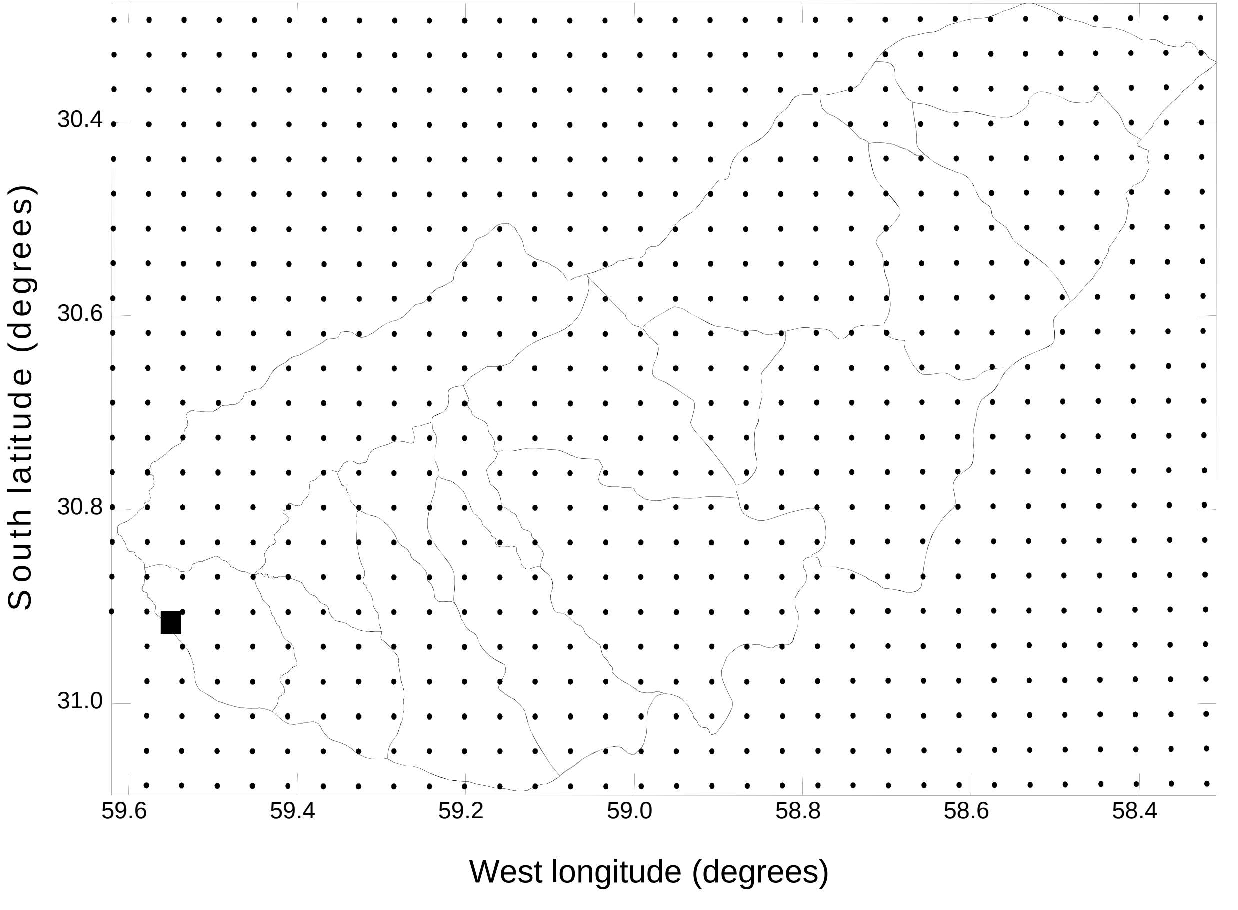
On the other hand: Satellite-based methods of rainfall estimation at a pixel unit are affected by significant errors at present, which depend on the type of rain among other factors.

Advantage over point observations:

They provide full spatial coverage (precipitation estimations can be performed at all pixels) and account for spatial variability of rainfall.

Therefore, they are more adequate to get the area-average rainfall over a sub-basin containing several to many pixels.

Location of pixel centers and Paso Medina station (outlet) over the watershed



Techniques to obtain accumulated precipitation estimates at a given pixel consist on two steps:

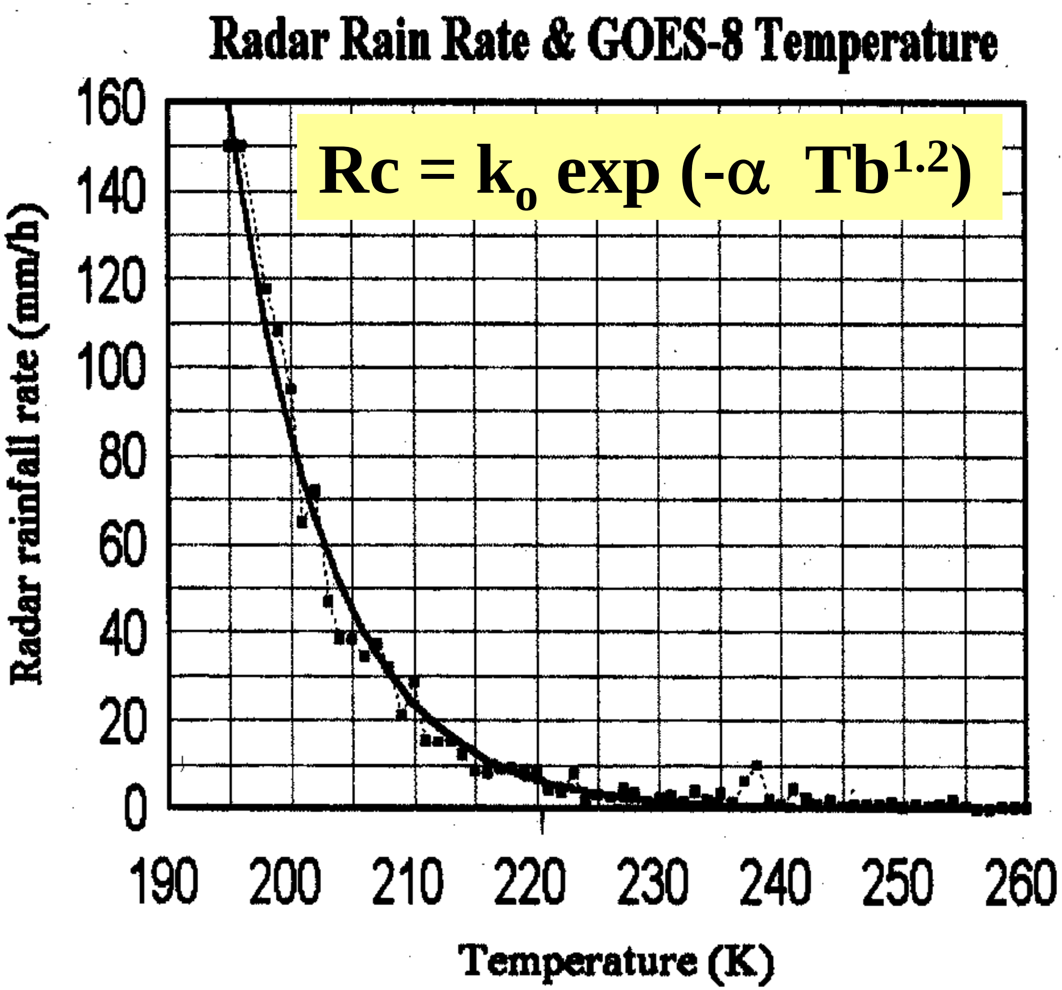
1. Estimation of mean spatial rain rate at every pixel

2. Time integration over a lapse assigned to the analyzed image

The Auto-estimator techique (Vicente, Scofield and Menzel, 1998) with further modifications is called Hydro-estimator (HE). A version of this technique was developed at the University of Buenos Aires and is run operationally at the National Meteorological Service of Argentina.

Auto-estimator technique: Designed to estimate convective rainfall in an operational way, accumulated on lapses lesser than 1 day, with a spatial resolution of 1 pixel (4km x 4km).

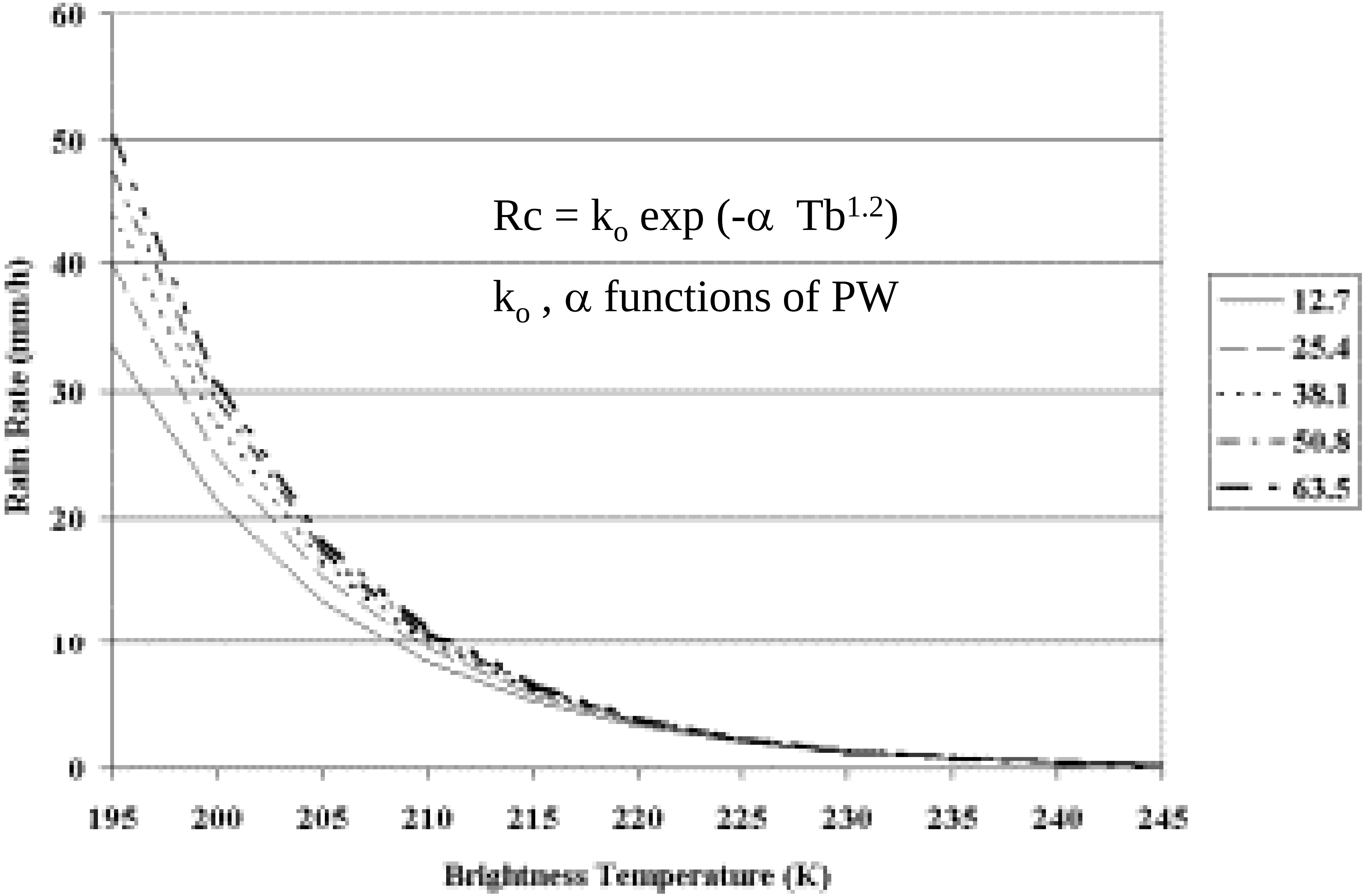
A power-law empirical function relates the brightness temperature at the cloud top with the rain rate at the cloud base



Vicente, Scofield and Menzel, 1998

The relationship applies to unicellular and multicell convective clouds (*cumuloninmbus)* at mature stage.

A further modification introduced the atmospheric precipitable water as a parameter → family of curves

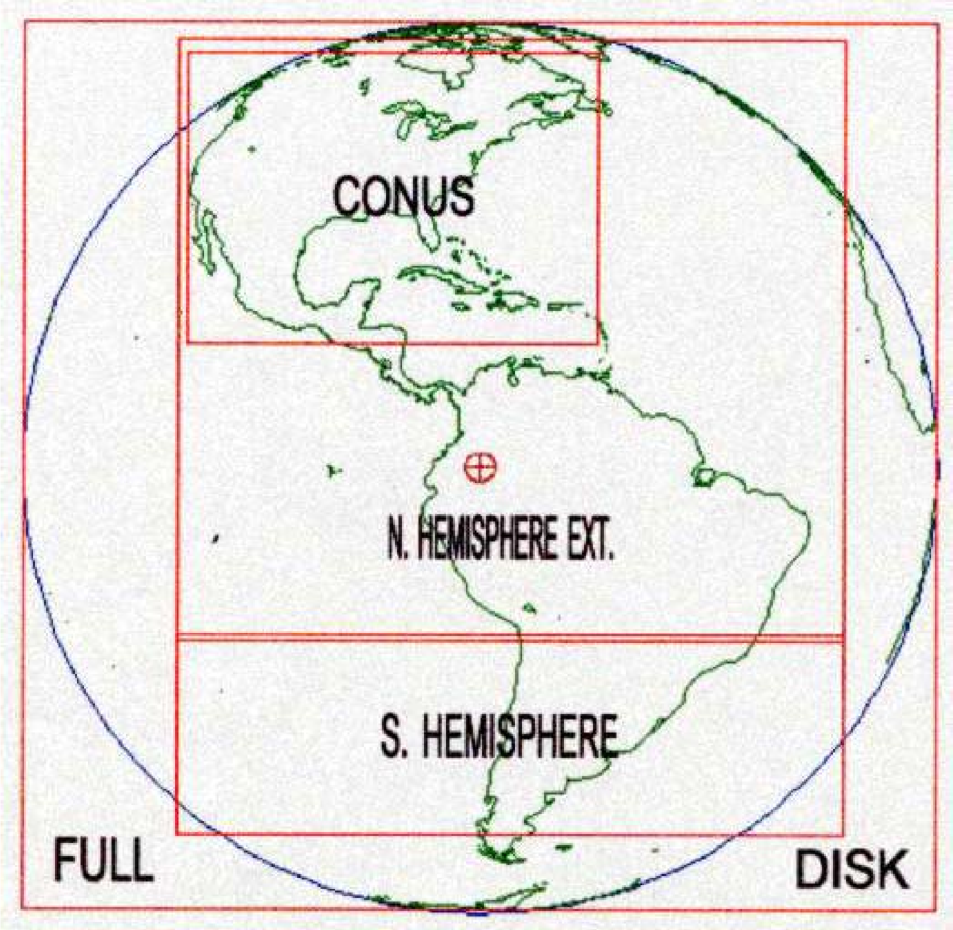


$Rc = k_o \exp(-\alpha\ Tb^{1.2})$

k_o , α functions of PW

(Scofield and Kuligowski, 2003)

Satellite GOES East: 4 sectors of images generation



Source: NOAA / NESDIS

Scanning frequency

CONUS: 1 every 15 minutes

SOUTHERN HEMISPHERE:

1 every 30 minutes over 70% of the time during the day.

1 every 90 minutes over the lasting 30% of the time.

To better describe the displacement of cloud systems and minimize the deformation in the obtained rainfall fields, it was proposed the generation of synthetic brightness temperature images interpolated between two consecutive observed images.

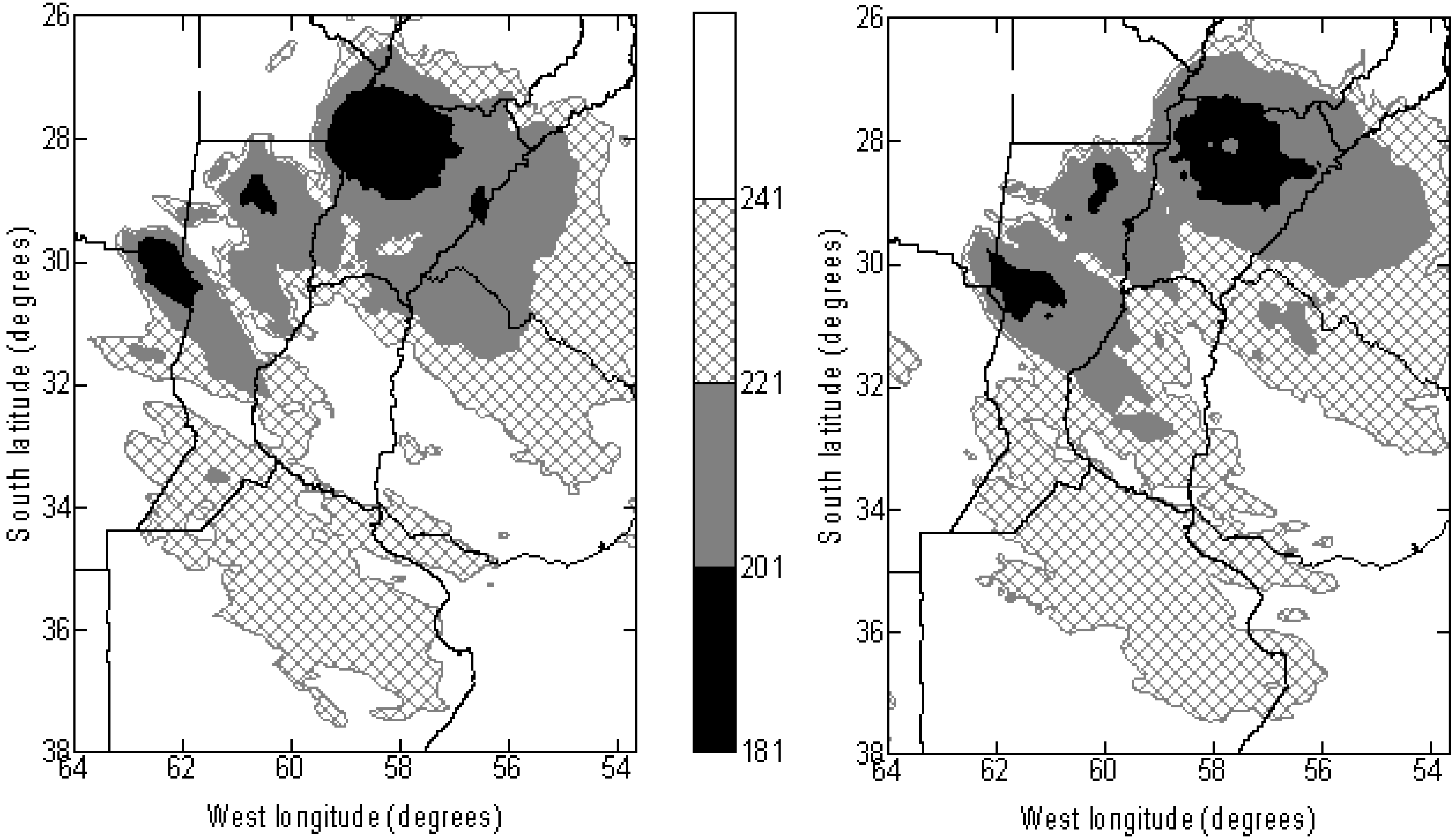
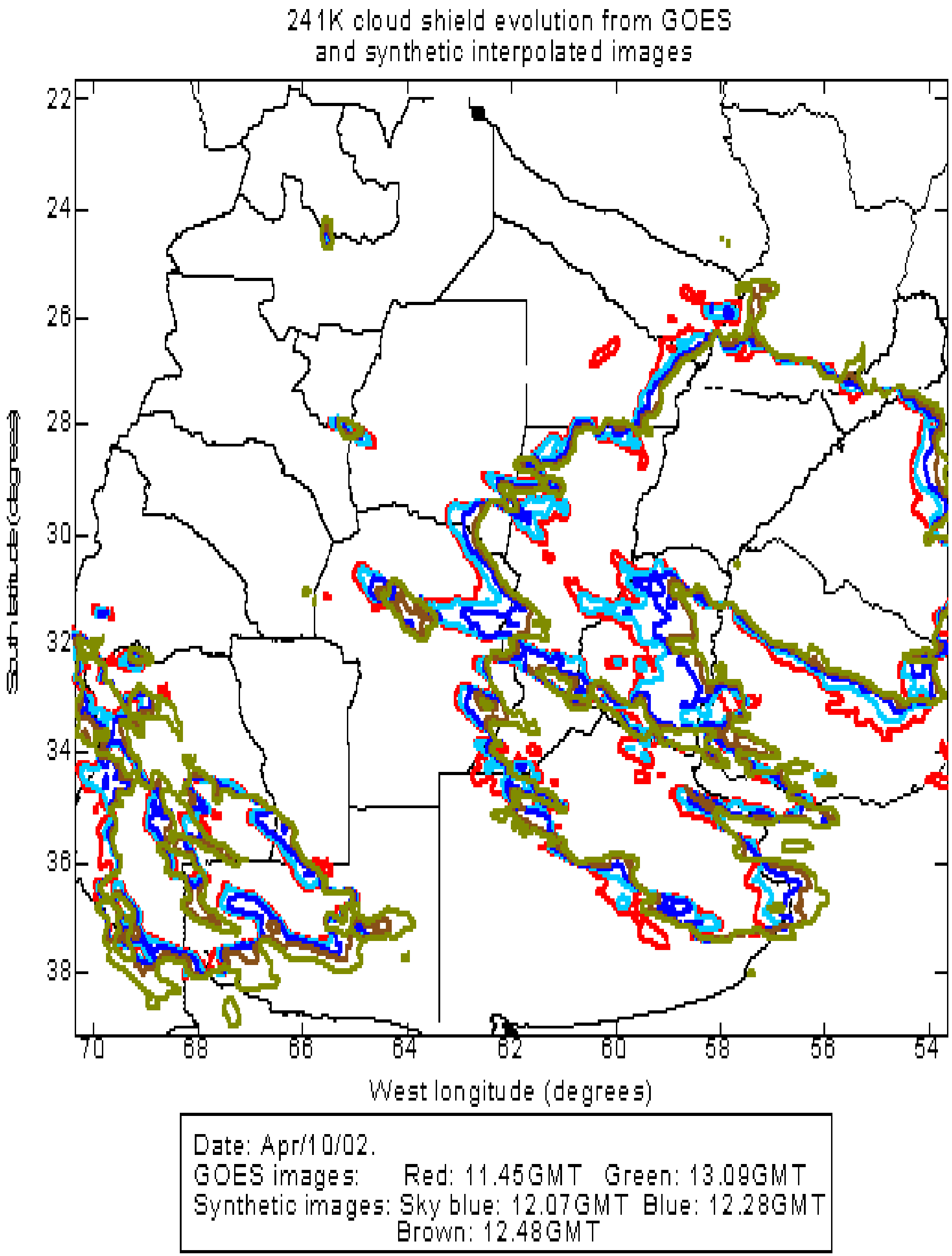


Figure 1. Bright temperature fields from two consecutive GOES IR images
Class interval limits are in Kelvin degrees
Date: Apr/10/02 Left: 11.45 UTC Right: 13.09 UTC

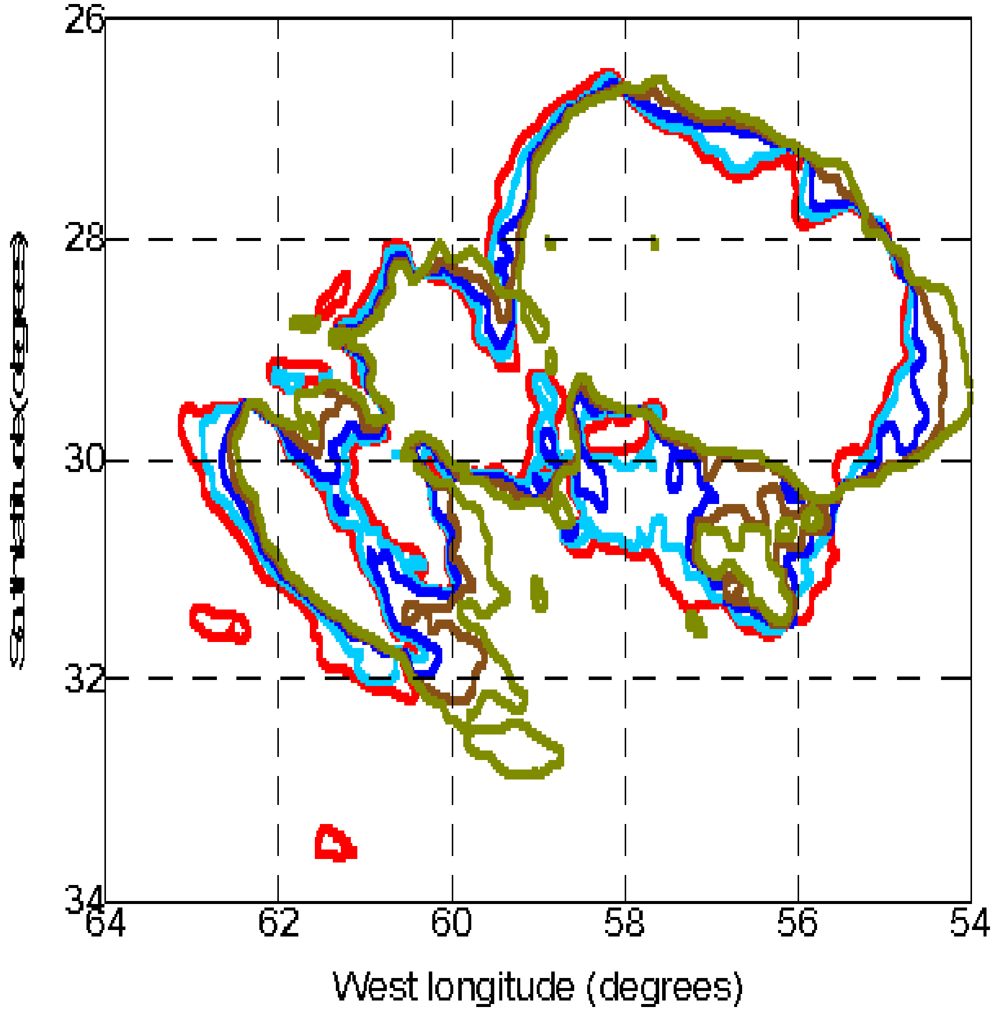
The image was sectorized in boxes of 4x4 degrees.

In order to determine the mean vector displacement of clouds on each box, two criteria were proposed, applied and tested. The vector difference (in pixel units) between pixels with cloud tops at the same tropospheric layer in both the analyzed and the precedent images was searched, which complies with one of the following conditions:

- The maximum cross-correlation coefficient of temperature values at pixels in two consecutive images; and
- The highest joint frequency of the same interval class of temperature (or same atmospheric layer) at pixels in two consecutive images.


241K cloud shield evolution from GOES
and synthetic interpolated images
22
24
26
28
30
32
34
36
38
South latitude (degrees)
70
68
66
64
62
60
58
56
54
West longitude (degrees)
Date: Apr/10/02.
GOES images: Red: 11.45GMT Green: 13.09GMT
Synthetic images: Sky blue: 12.07GMT Blue: 12.28GMT
Brown: 12.48GMT

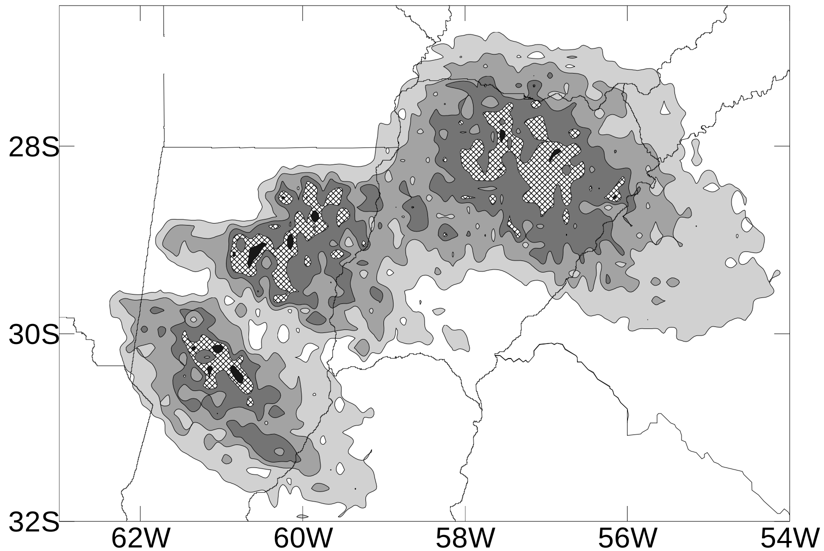
221K cloud shield evolution from GOES
and synthetic interpolated images

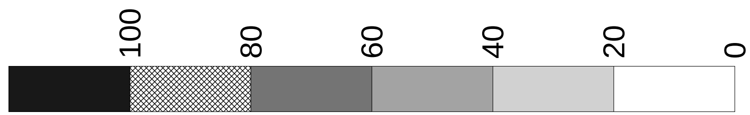


Date: Apr/10/02.
GOES images: Red: 11.45GMT Green: 13.09GMT
Synthetic images: Sky blue: 12.07GMT Blue: 12.28GMT
Brown: 12.48GMT

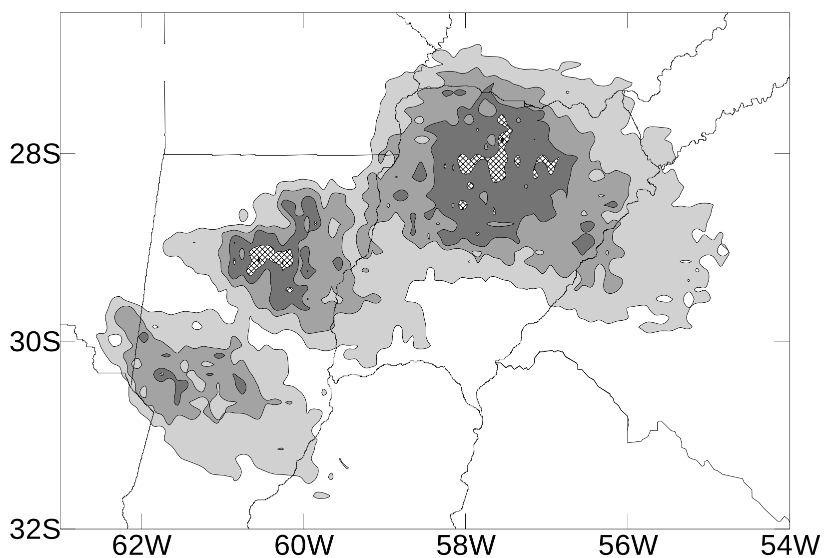
Storm of April 10, 2002

Isoyetal map obtained from GOES images (procedure 1) (6hr period)



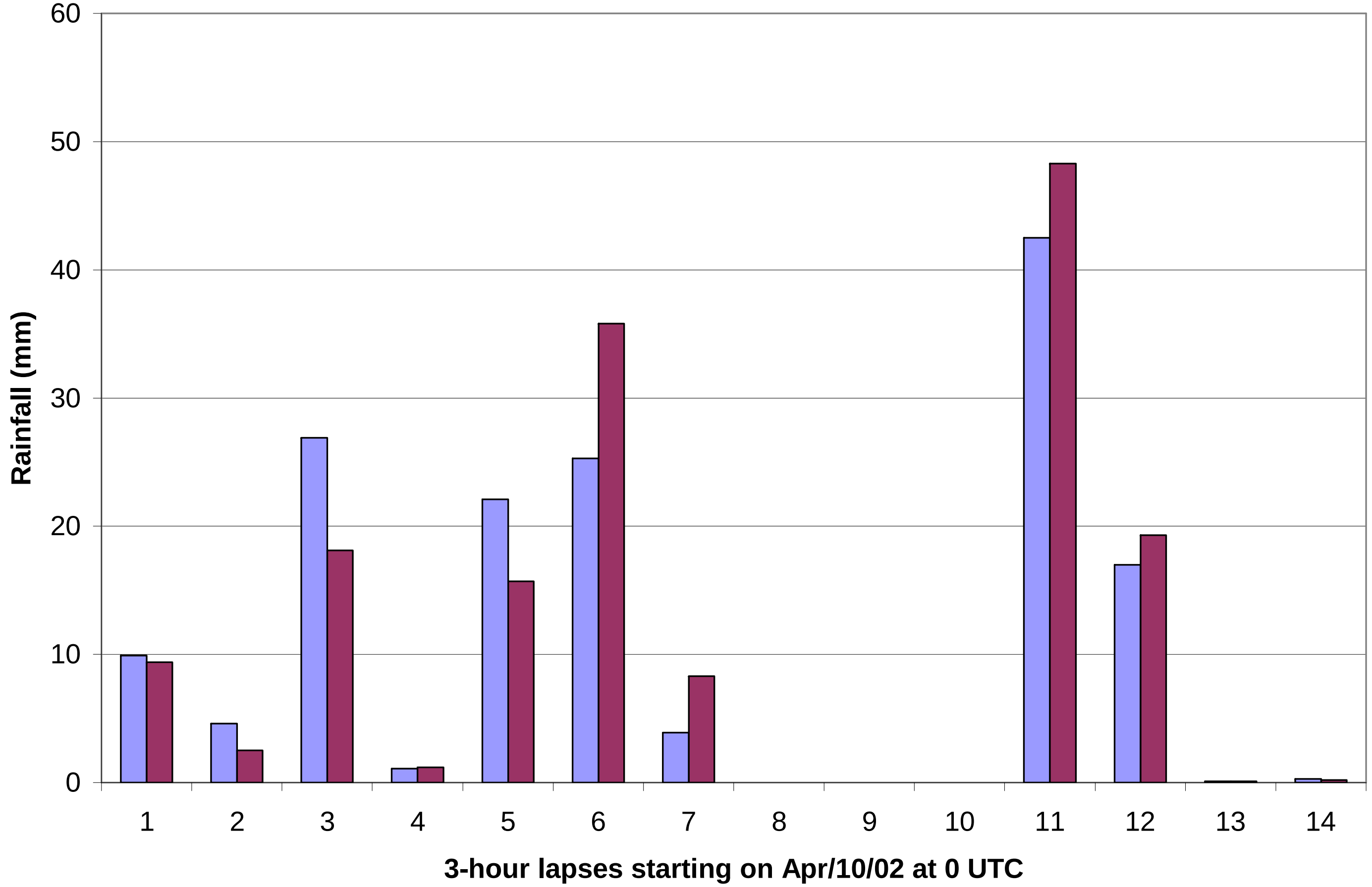


Isoyetal map obtained from GOES plus synthetic images (procedure 2) (same period)

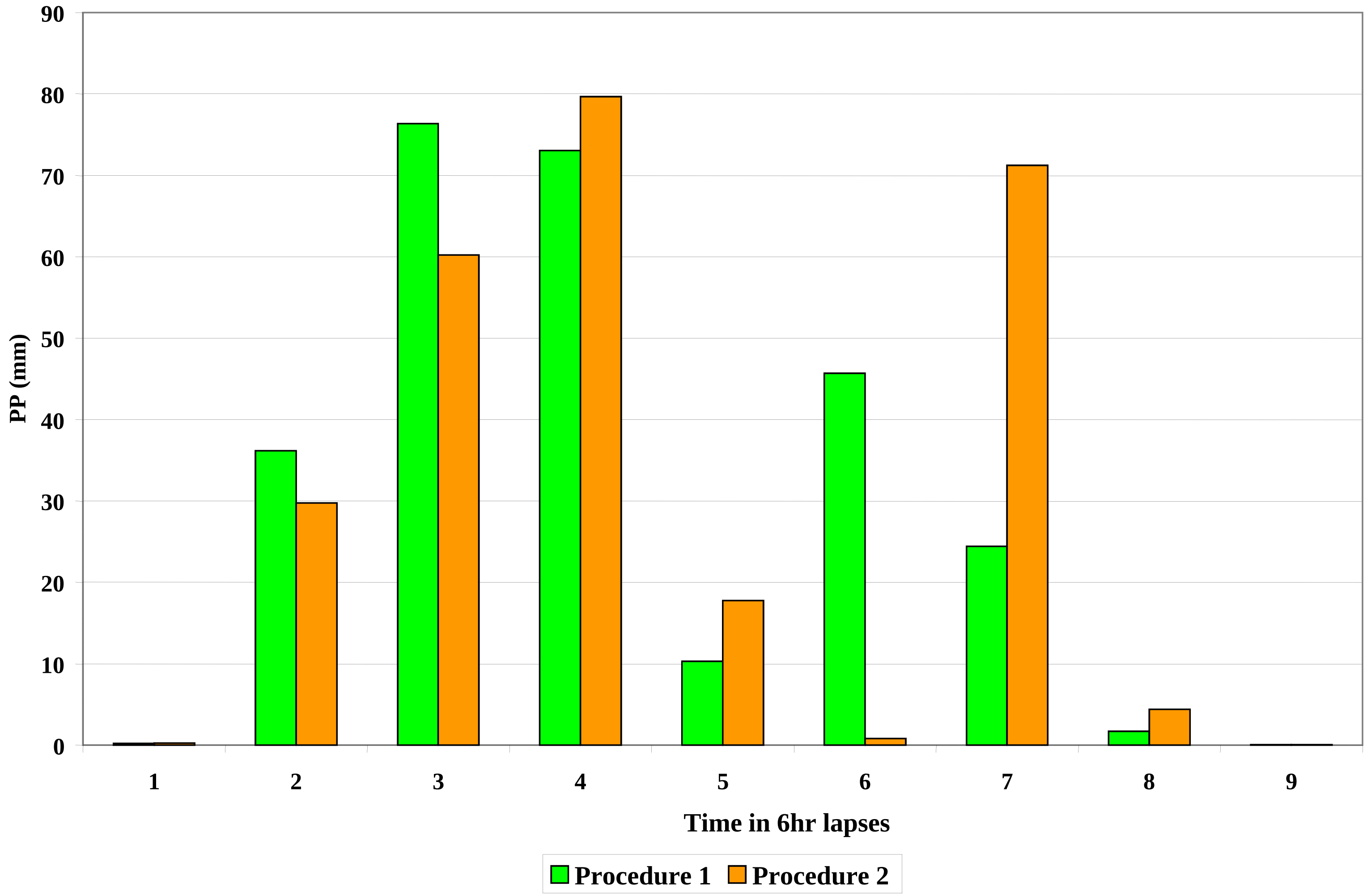


Estimated area-averaged rainfall over sub-basin 13

Left bars: Procedure 1 Right bars: Procedure 2



6-hour lapses evolution of area-averaged rainfall. Procedure 1 and Procedure 2



OCINE2 Rainfall-Runoff Model

It is a conceptual, pseudo-distributed parameters model developed by the project team, which computes both overland flows and stream flows by applying the *kinematic wave theory.*

Basic equations

$$\frac{\partial Q}{\partial x} + \frac{\partial A}{\partial t} = q$$

Continuity for stream segment

$$\frac{\partial y}{\partial t} + \frac{\partial q}{\partial x} = p - f$$

Continuity for catchment segment

$$Q = \alpha_s * A^{m_s}$$

Momentum for stream segment

$$q = \alpha_c * y^{m_c}$$

Momentum for catchment segment

x: distance along the stream segment (m); Q: runoff in the stream segment (m3/sec) ; A: area of the wetted stream cross-section (m2) ; q: discharge per unit width in the catchment segment (m2/sec); y: average depth of flow (m); p: rainfall rate (mm/hr); f: infiltration rate (mm/h);

α_c, m_c, α_s, m_s, are calibration parameters for the catchment and stream segments, respectively.

APPLICATION TO THE FELICIANO RIVER BASIN WITH OUTLET IN PASO MEDINA STATION

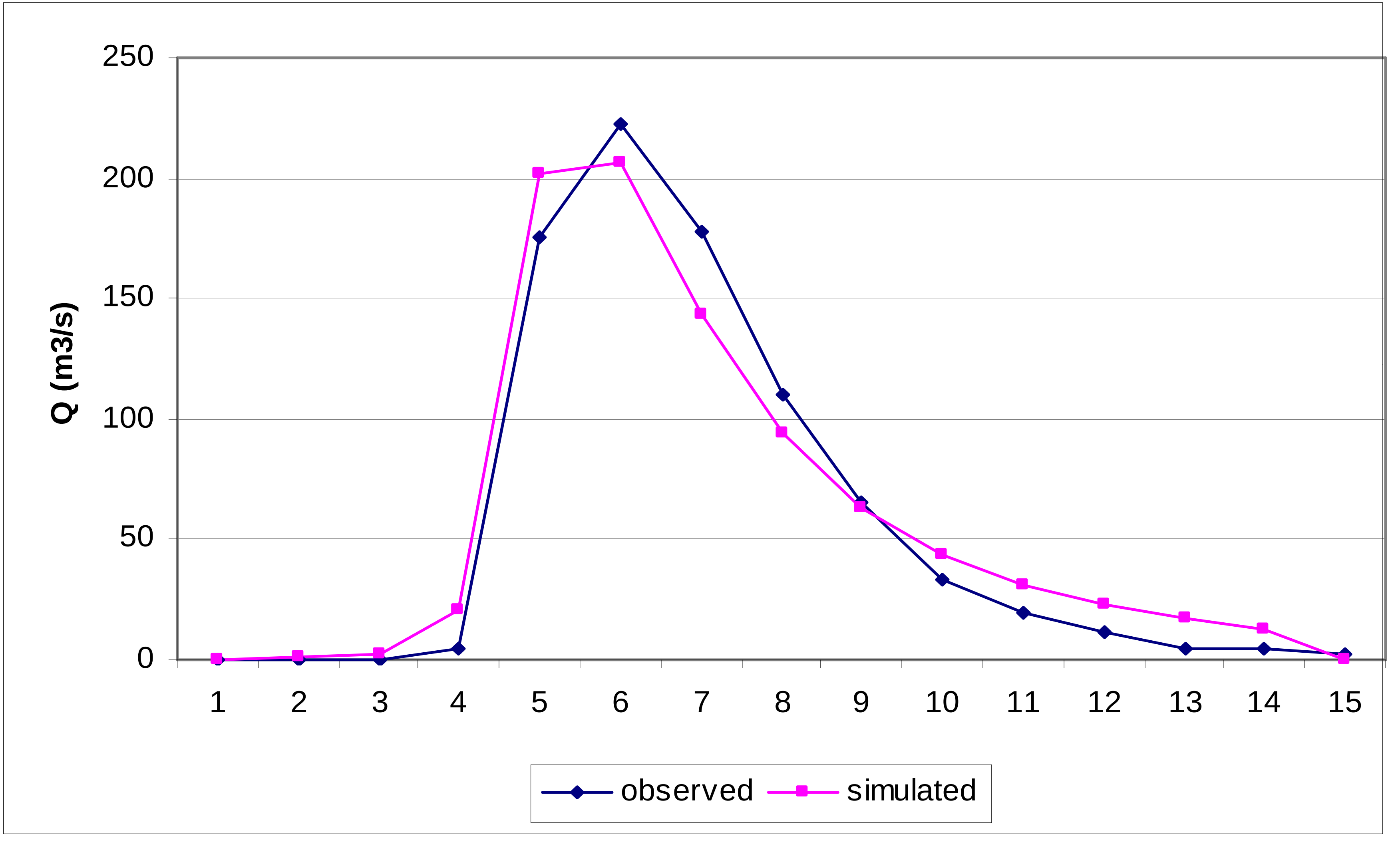
As part of the calibration process, a segmentation in 17 sub-basins was performed after an analysis of the dynamics of hydrological responses to rainfall inputs.

A Topologic framework with 51 segments (34 for overland flow and 17 for stream flow) was utilized.

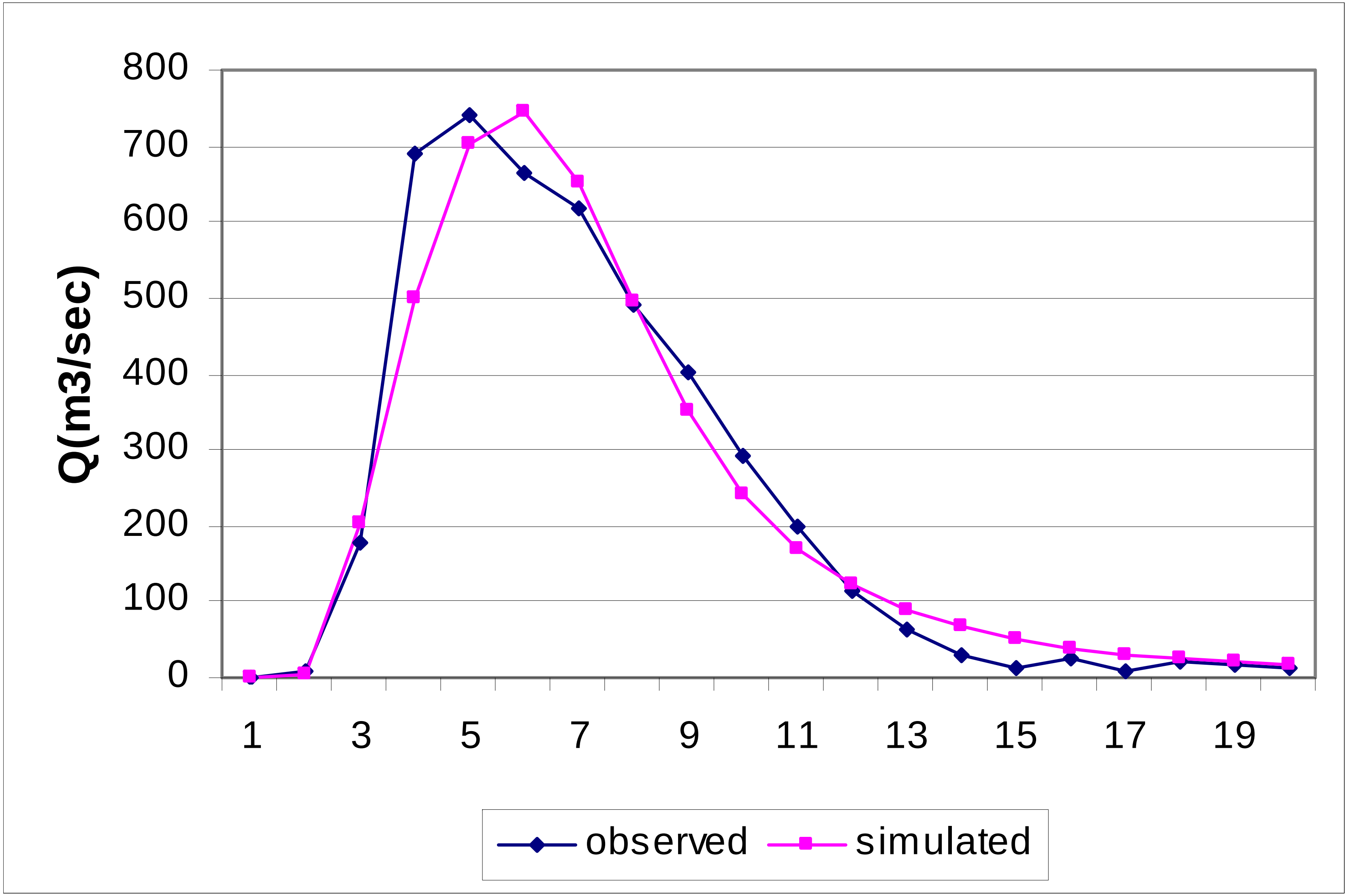
Storm hydrographs modelled.

Due to a lack of information about soil characteristics and soil moisture conditions previous to the storm to be modelled, it is not possible at this stage to predict the runoff component of the rainfall. Therefore, for each of the cases modelled, the volume of the simulated hydrograph has been adjusted to match the volume of the observed hydrograph in order to evaluate the model skill in predicting the distribution of that runoff in time, that is, the shape of the storm hydrograph.

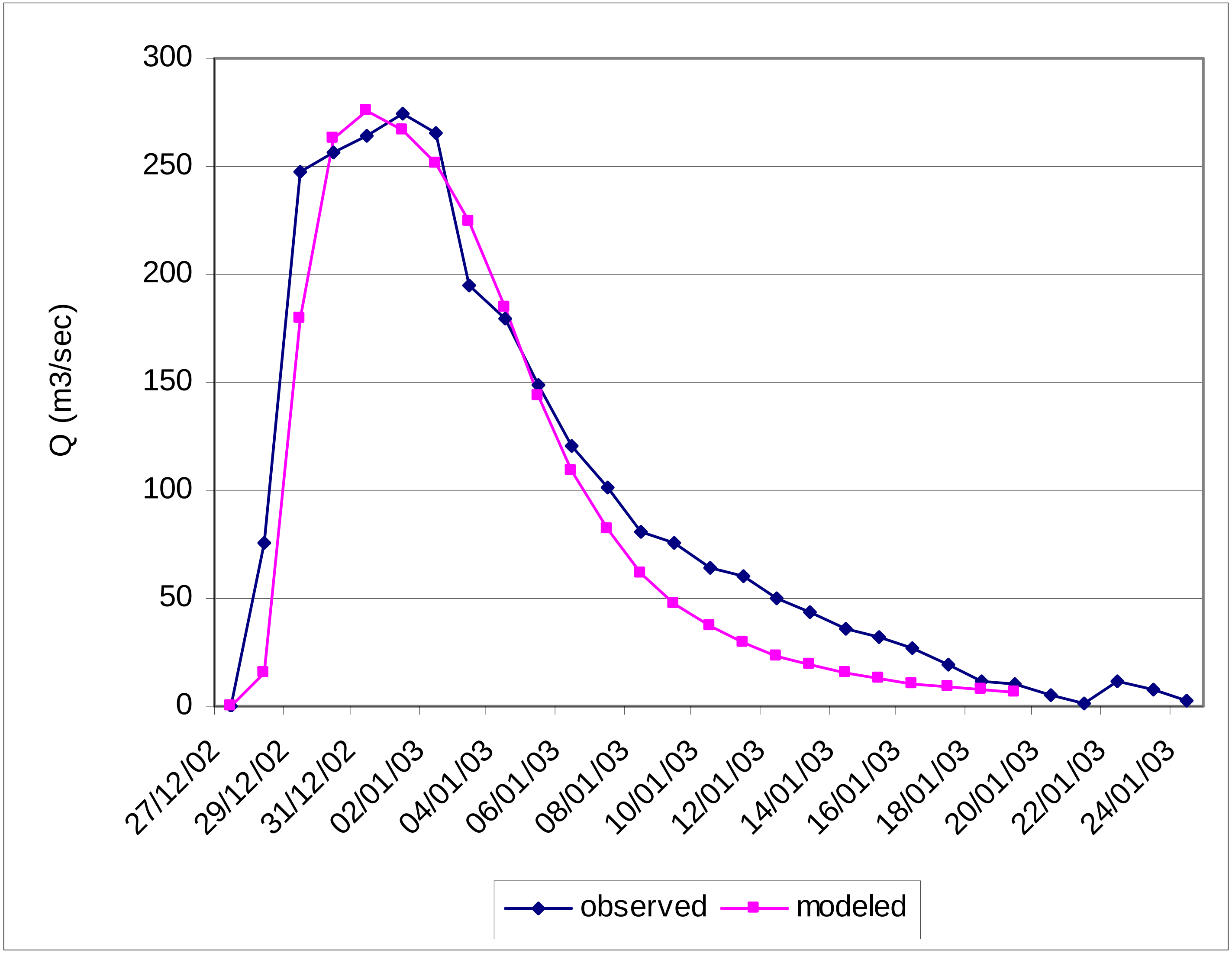
Observed and simulated hydrographs
Storm starting on April 9, 2002



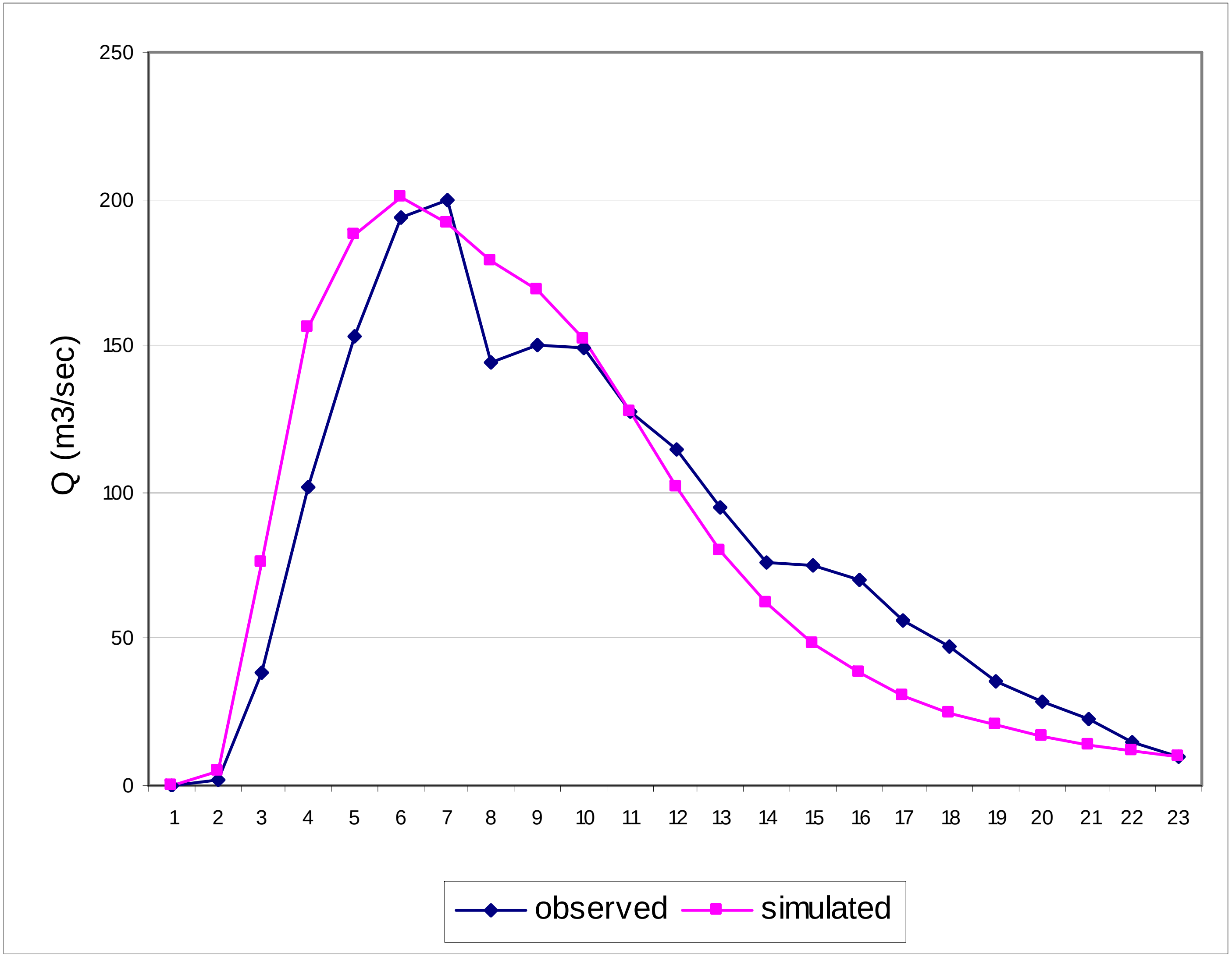
Observed and simulated hydrographs
Storm starting on April 22, 2002



Observed and simulated hydrographs
Storm starting on December 28, 2002

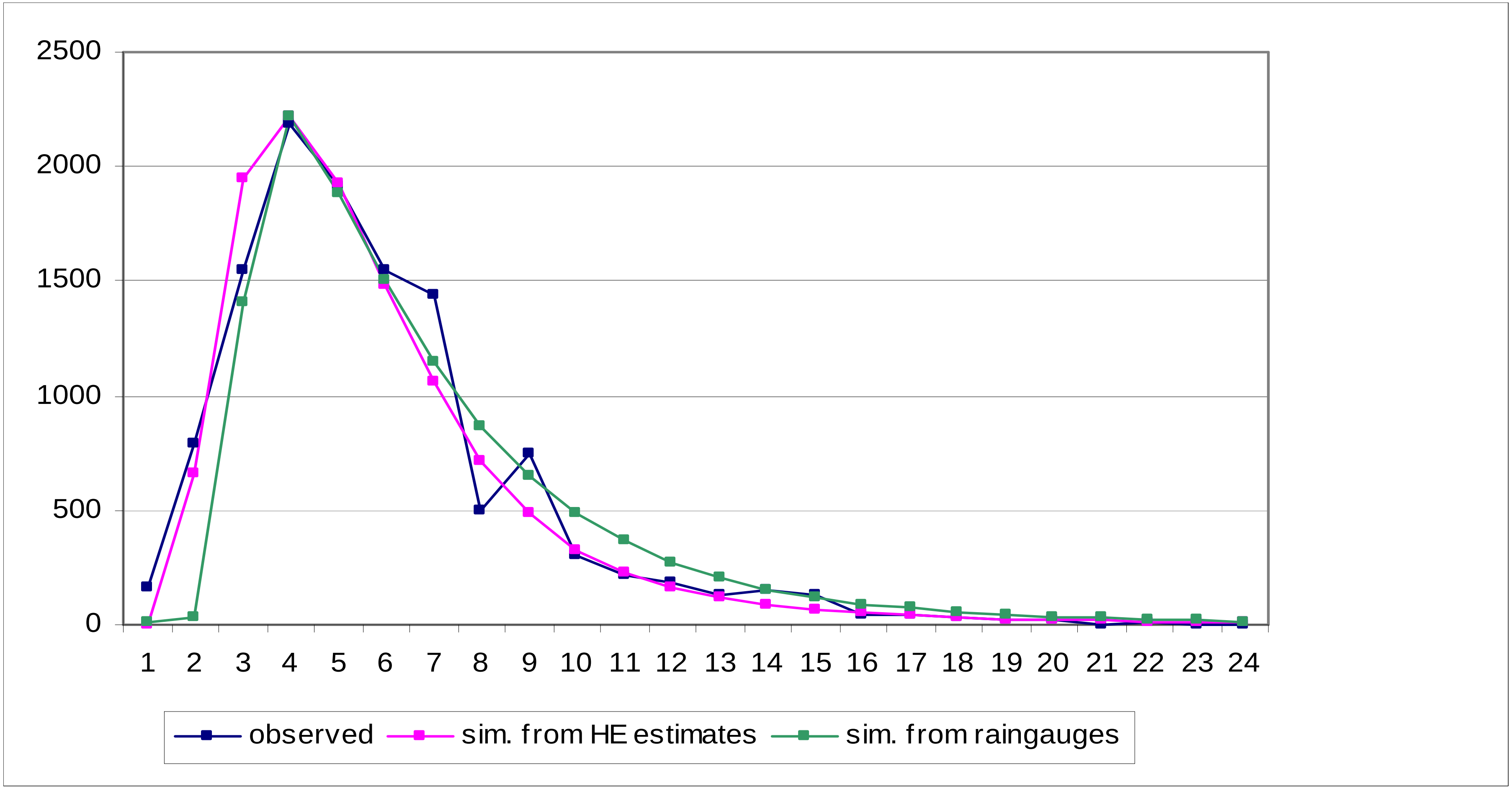


Observed and simulated hydrographs
Storm starting on March 9, 2003



Observed and simulated hydrographs

Storm starting on April 23, 2003



CONCLUSIONS

- HE estimates lead to compute area-averaged rainfall over large sub-basins which are as good as the ones obtained from conventional raingauge networks to be used as input in rainfall-runoff models.

- The present state-of-the-art permits to implement operational hydrological forecast systems in ungauged basins of developing countries, based on satellite rainfall estimates as model inputs.

Thank you