PRECIPITATION DOWNSCALING:

METHODOLOGIES AND HYDROLOGIC APPLICATIONS

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DOWNSCALING

- ✓ Downscaling = "Creating" information at scales smaller than the available scales, or reconstructing variability at sub-grid scales. It is usually statistical in nature, i.e., statistical downscaling.

- ✓ Could be seen as equivalent to "conditional simulation" i.e, simulation conditional on preserving the statistics at the starting scale and/or other information.

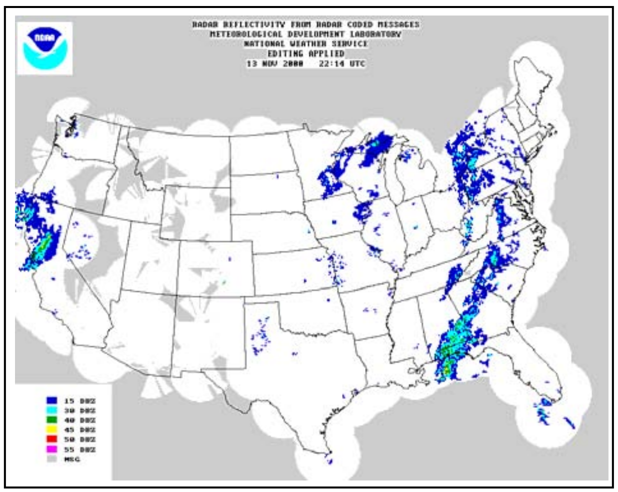
PREMISES OF STATISTICAL DOWNSCALING

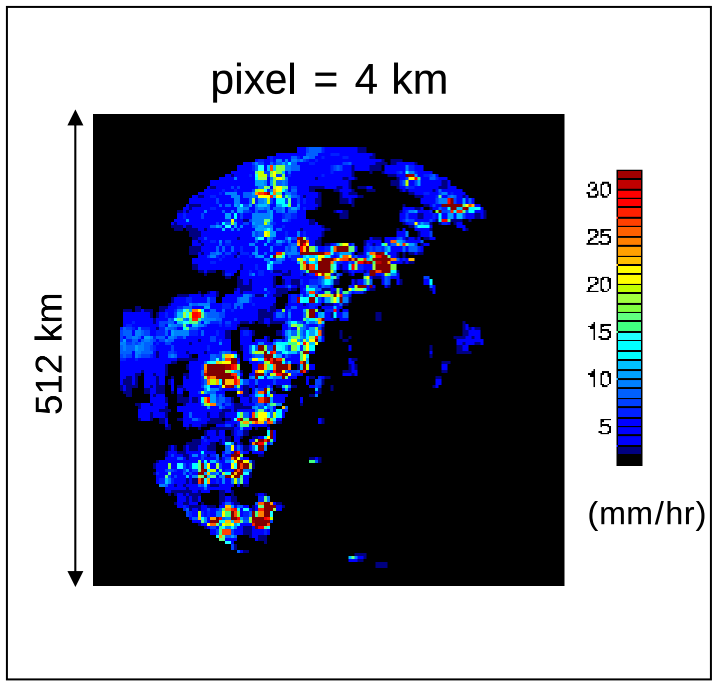
- ✓ Precipitation exhibits space-time variability over a large range of scales (a few meters to thousand of Kms and a few seconds to several decades)

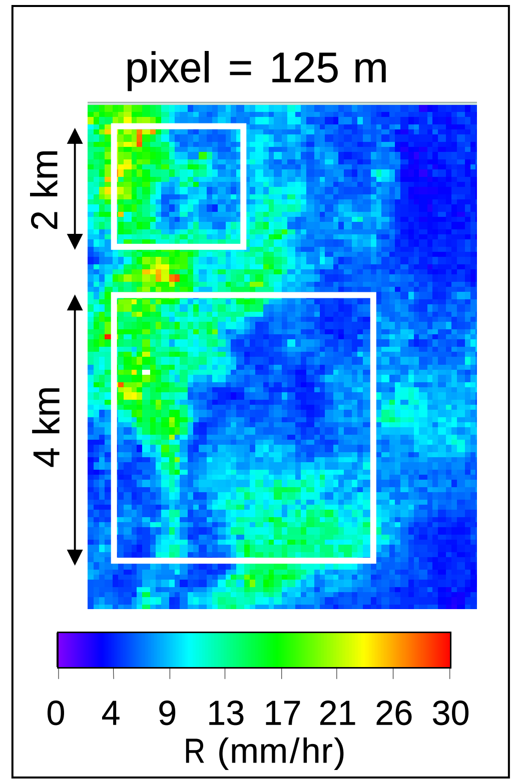
- ✓ There is a substantial evidence to suggest that despite the very complex patterns of precipitation, there is an underlying simpler structure which exhibits scale-invariant statistical characteristics

- ✓ If this scale invariance is unraveled and quantified, it can form the basis of moving up and down the scales: important for efficient and parsimonious downscaling methodologies

Precipitation exhibits spatial variability at a large range of scales







OUTLINE OF TALK

1. Multi-scale analysis of spatial precipitation
2. A spatial downscaling scheme
3. Relation of physical and statistical parameters for real-time or predictive downscaling
4. A space-time downscaling scheme
5. Hydrologic applications

References

1. Kumar, P., E. Foufoula-Georgiou, A multicomponent decomposition of spatial rainfall fields 1. Segregation of large- and small-scale features using wavelet tranforms, 2. Self-similarity in fluctuations, *Water Resour. Res.*, 29(8), 2515-2532, doi: 10.1029/93WR00548, 1993.
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3. Perica, S., E. Foufoula-Georgiou, Linkage of Scaling and Thermodynamic Parameters of Rainfall: Results From Midlatitude Mesoscale Convective Systems, *J. Geophys. Res.*, 101(D3), 7431-7448, doi: 10.1029/95JD02372, 1996.
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6. Nykanen, D. and E. Foufoula-Georgiou, Soil moisture variability and its effect on scale-dependency of nonlinear parameterizations in coupled land-atmosphere models, *Advances in Water Resources*, 24(9-10), 1143-1157, doi: 2001.10.1016/S0309-1708(01)00046-X, 2001
7. Nykanen, D. K., E. Foufoula-Georgiou, and W. M. Lapenta, Impact of small-scale rainfall variability on larger-scale spatial organization of land–atmosphere fluxes, *J. Hydrometeor.*, 2, 105–120, doi: 10.1175/1525-7541(2001)002, 2001

1. Multiscale analysis – 1D example

$$\{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\}$$

$$X_0 \equiv \bar{X}_0$$

$$\underbrace{\frac{x_1+x_2}{2} \quad \frac{x_3+x_4}{2} \quad \frac{x_5+x_6}{2} \quad \frac{x_7+x_8}{2}}_{\bar{X}_1}$$

$$\underbrace{\frac{x_1+x_2+x_3+x_4}{4} \qquad \frac{x_5+x_6+x_7+x_8}{4}}_{\bar{X}_2}$$

$$\underbrace{\frac{x_1+x_2+x_3+x_4+x_5+x_6+x_7+x_8}{8}}_{\bar{X}_3}$$

1. Multiscale analysis – 1D example

$$\{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\}$$

$$X_0 \equiv \bar{X}_0$$

$$\underbrace{\frac{x_1+x_2}{2} \quad \frac{x_3+x_4}{2} \quad \frac{x_5+x_6}{2} \quad \frac{x_7+x_8}{2}}_{\bar{X}_1} \qquad \underbrace{\frac{x_1-x_2}{2} \quad \frac{x_3-x_4}{2} \quad \frac{x_5-x_6}{2} \quad \frac{x_7-x_8}{2}}_{X_1'}$$

$$\underbrace{\frac{x_1+x_2+x_3+x_4}{4} \quad \frac{x_5+x_6+x_7+x_8}{4}}_{\bar{X}_2} \qquad \underbrace{\frac{x_1+x_2-(x_3+x_4)}{4} \quad \frac{x_5+x_6-(x_7+x_8)}{4}}_{X_2'}$$

$$\underbrace{\frac{x_1+x_2+x_3+x_4+x_5+x_6+x_7+x_8}{8}}_{\bar{X}_3} \qquad \underbrace{\frac{x_1+x_2+x_3+x_4-(x_5+x_6+x_7+x_8)}{8}}_{X_3'}$$

1. Multiscale analysis – 1D example

$$\{x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8\}$$

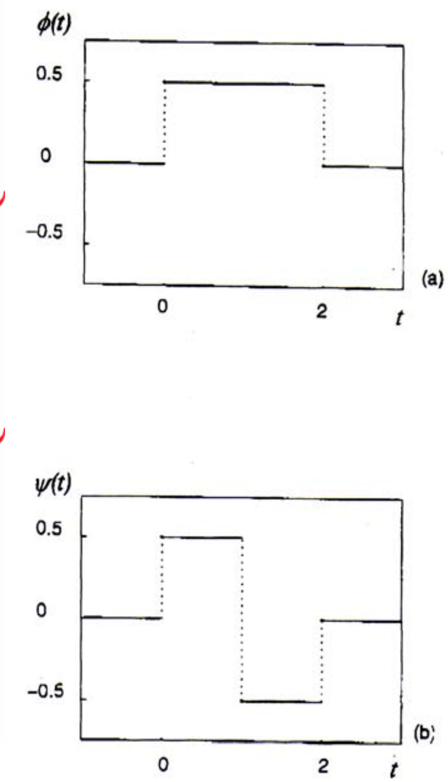
$$X_0 \equiv \bar{X}_0$$

$$\underbrace{\frac{x_1+x_2}{2} \quad \frac{x_3+x_4}{2} \quad \frac{x_5+x_6}{2} \quad \frac{x_7+x_8}{2}}_{\bar{X}_1} \qquad \underbrace{\frac{x_1-x_2}{2} \quad \frac{x_3-x_4}{2} \quad \frac{x_5-x_6}{2} \quad \frac{x_7-x_8}{2}}_{X'_1}$$

$$\underbrace{\frac{x_1+x_2+x_3+x_4}{4} \quad \frac{x_5+x_6+x_7+x_8}{4}}_{\bar{X}_2} \qquad \underbrace{\frac{x_1+x_2-(x_3+x_4)}{4} \quad \frac{x_5+x_6-(x_7+x_8)}{4}}_{X'_2}$$

$$\underbrace{\frac{x_1+x_2+x_3+x_4+x_5+x_6+x_7+x_8}{8}}_{\bar{X}_3} \qquad \underbrace{\frac{x_1+x_2+x_3+x_4-(x_5+x_6+x_7+x_8)}{8}}_{X'_3}$$

Haar Wavelet
Multiscale Filter:



Multiscale analysis via Wavelets

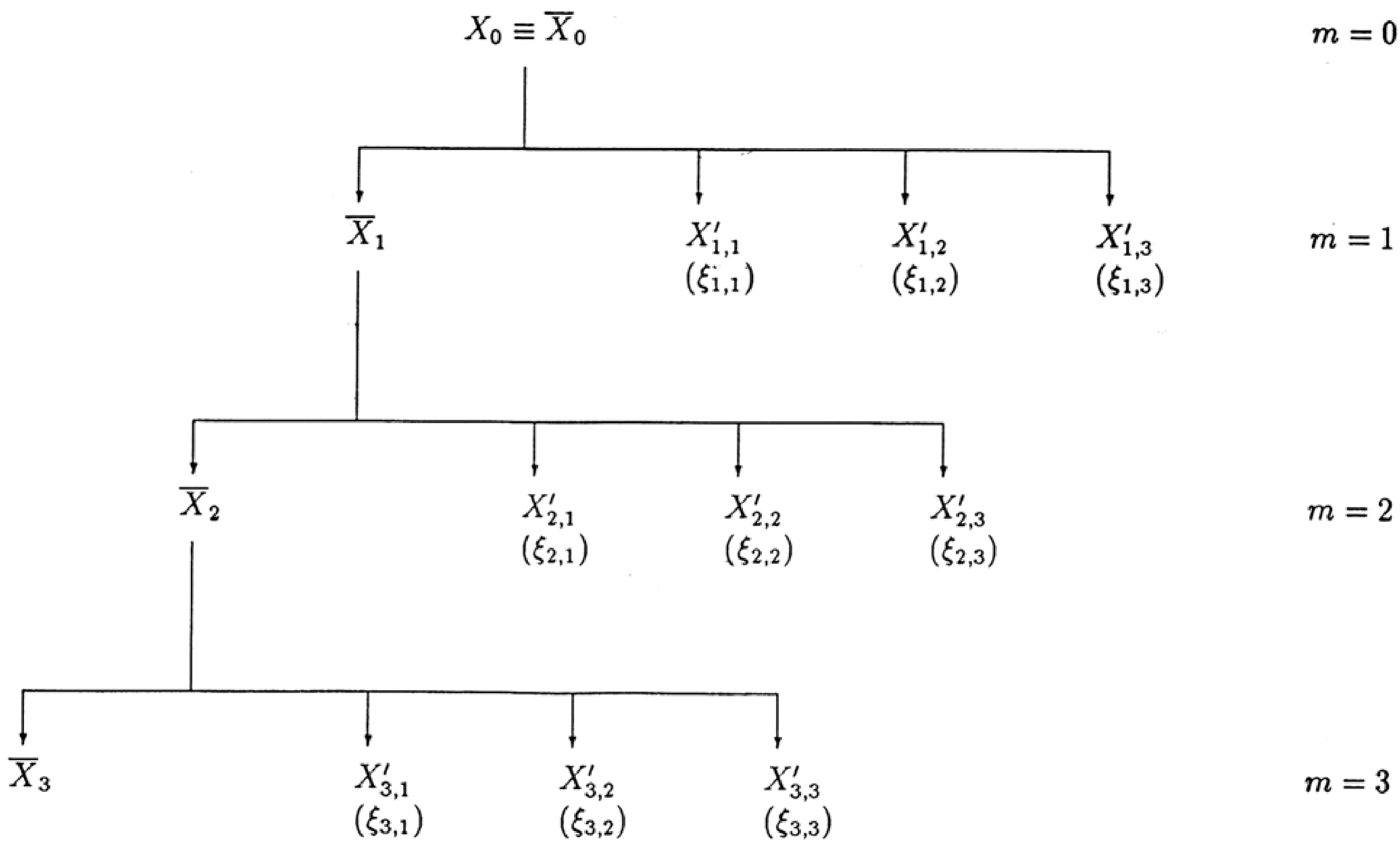
- ✓ Averaging and differencing at multiple scales can be done efficiently via a discrete orthogonal wavelet transform (WT), e.g., the Haar wavelet

- ✓ The inverse of this transform (IWT) allows efficient reconstruction of the signal at any scale given the large scale average and the “fluctuations” at all intermediate smaller scales

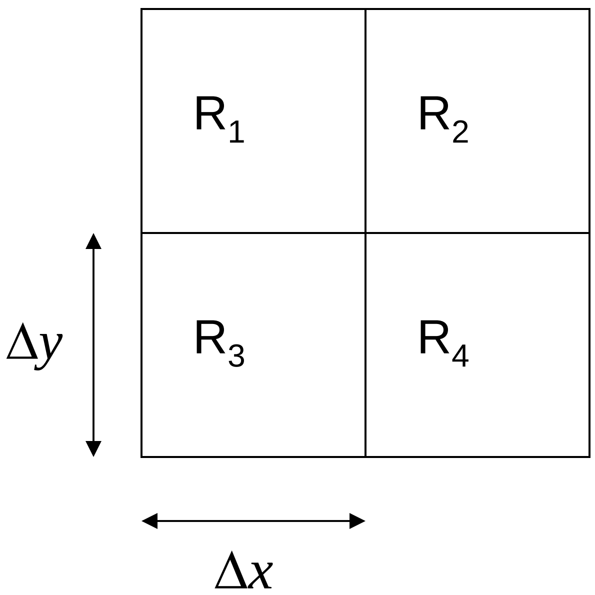
- ✓ It is easy to do this analysis in any dimension (1D, 2D or 3D).

(See Kumar and Foufoula-Georgiou, 1993)

Multiscale analysis – 2D example



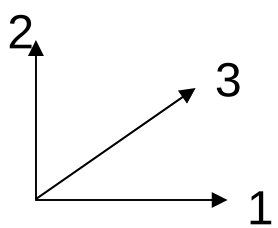
Interpretation of directional fluctuations (gradients)



$$X_1' = \frac{1}{2}\left[\left(\frac{R_2 - R_1}{\Delta x}\right) + \left(\frac{R_4 - R_3}{\Delta x}\right)\right] \cong \frac{\partial R}{\partial x}$$

$$X_2' = \frac{1}{2}\left[\left(\frac{R_4 - R_2}{\Delta y}\right) + \left(\frac{R_3 - R_1}{\Delta y}\right)\right] \cong \frac{\partial R}{\partial y}$$

$$X_3' = \frac{1}{2}\left[\left(\frac{R_1 - R_4}{\Delta l}\right) + \left(\frac{R_2 - R_3}{\Delta l}\right)\right] \cong \frac{\partial^2 R}{\partial x \partial y}$$



$$\Delta l = \sqrt{\Delta x^2 + \Delta y^2}$$

(See Kumar and Foufoula-Georgiou, 1993)

Observation 1

(See Perica and Foufoula-Georgiou, 1996)

- ✓ Local rainfall gradients ($X'_{m,i=1,2,3}$) depend on local average rainfall intensities $\overline{X}_m$ and were hard to parameterize

- ✓ But, standardized fluctuations $\xi_{m,i=1,2,3} = \dfrac{X'_{m,i=1,2,3}}{\overline{X}_m}$

  - ➢ are approximately independent of local averages
  - ➢ obey approximately a Normal distribution centered around zero, i.e, have only 1 parameter to worry about in each direction

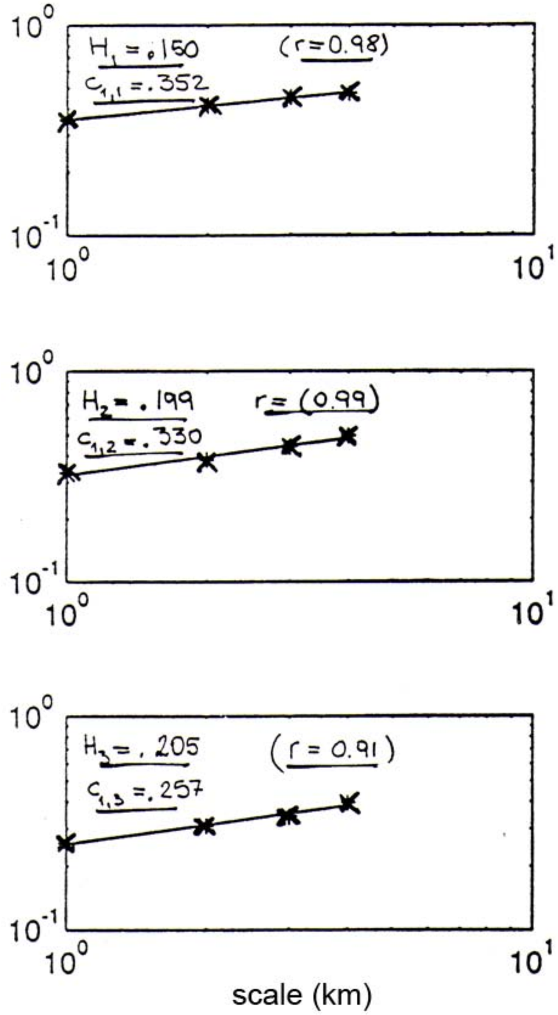
$$\text{At scale m:} \quad \sigma_{\xi_1}\ ,\ \sigma_{\xi_2}\ ,\ \sigma_{\xi_3}$$

Observation 2

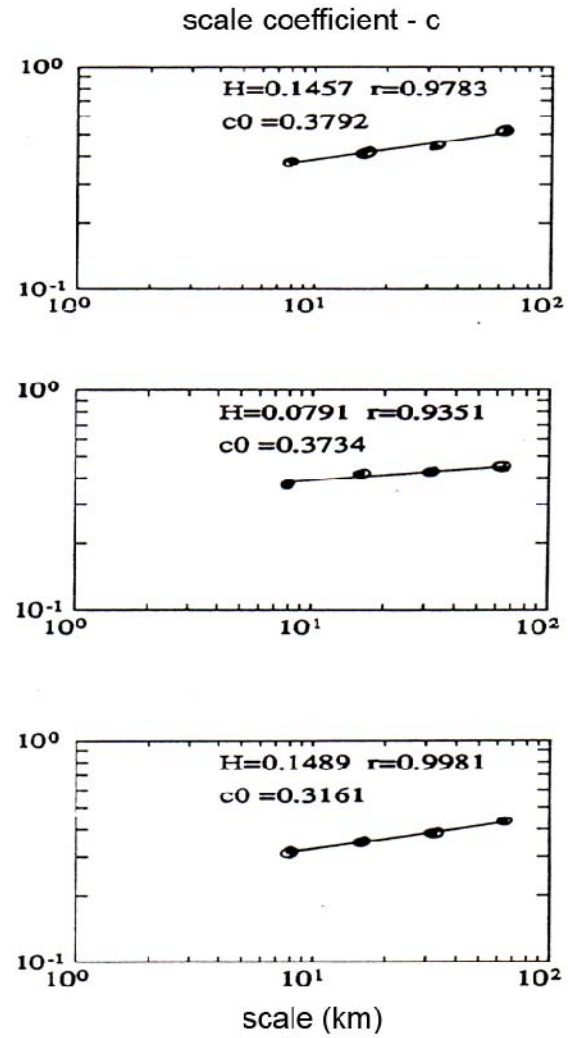
σ_{ξ_1} :

σ_{ξ_2} :

σ_{ξ_3} :



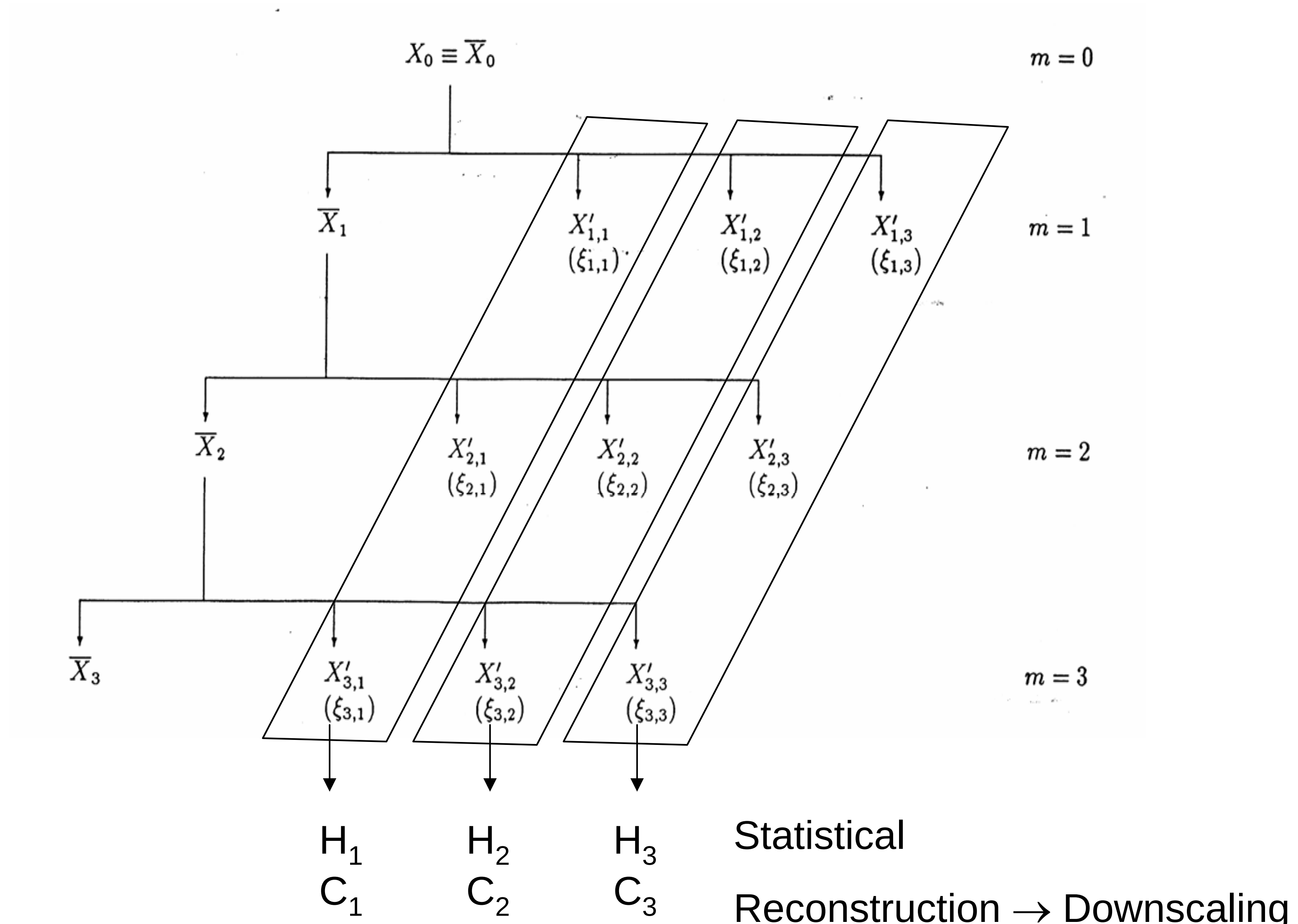
May 13, 1985, 1248 UTC



June 11, 1985, 0300 UTC

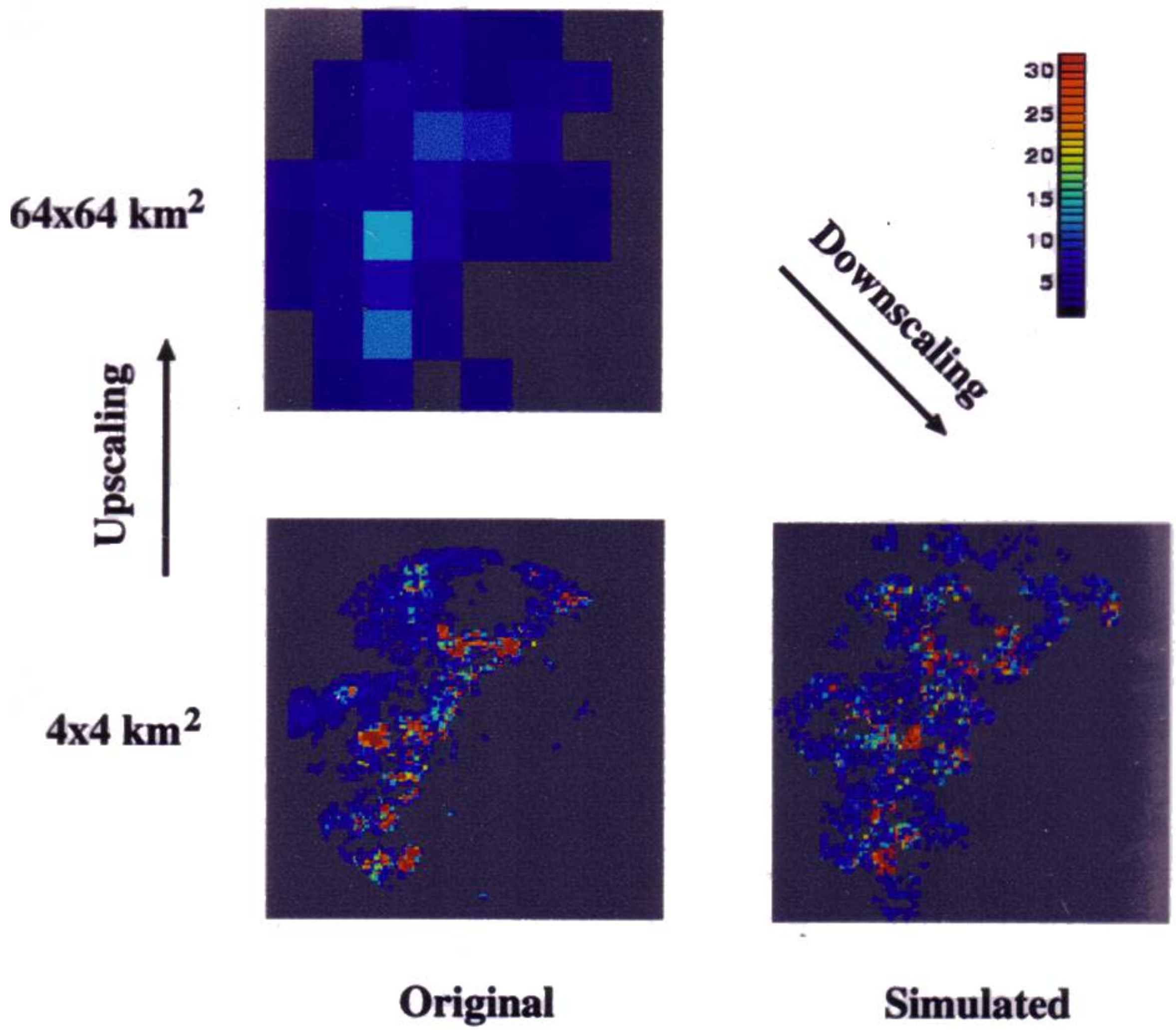
(See Perica and Foufoula-Georgiou, 1996)

2. Spatial downscaling scheme

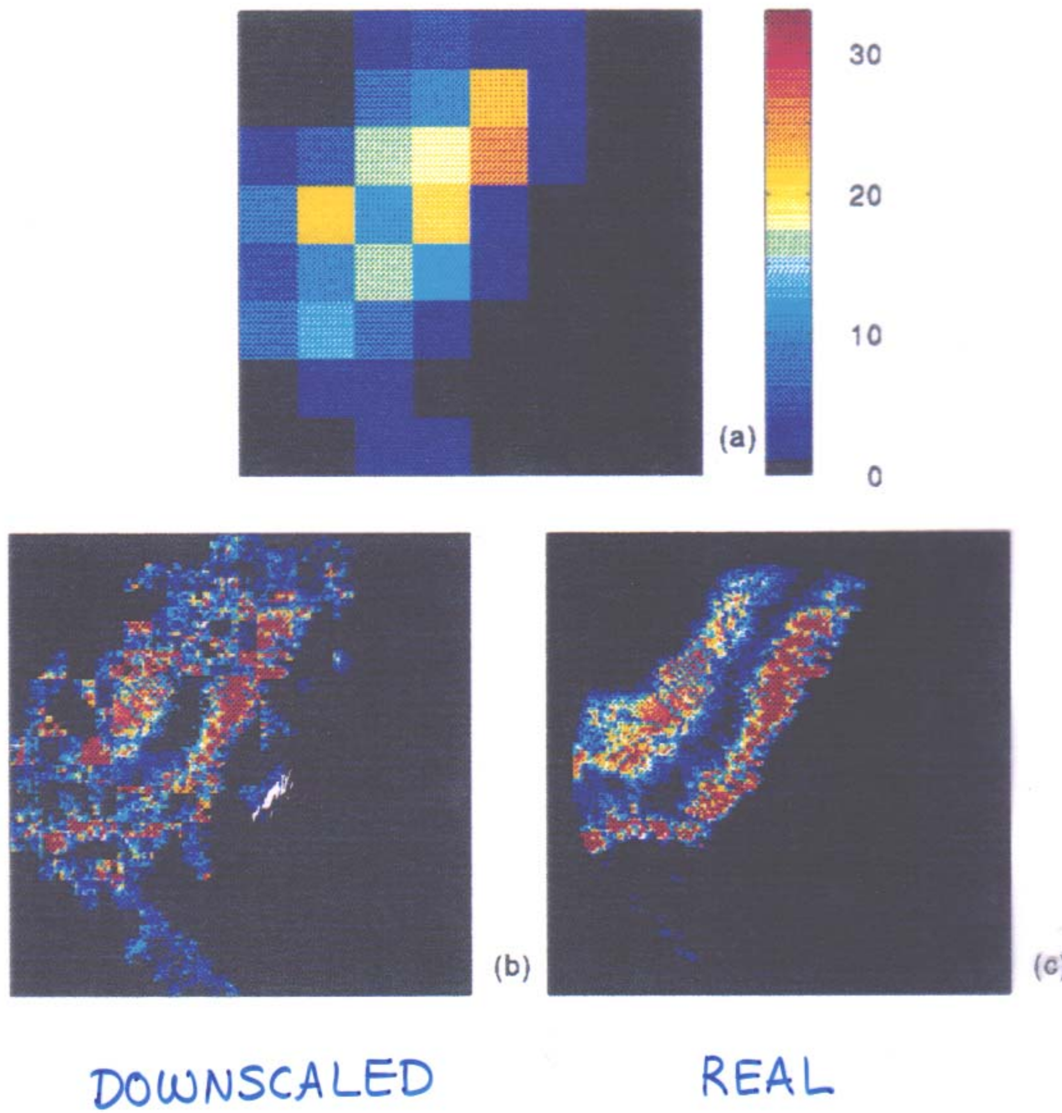


(See Perica and Foufoula-Georgiou, 1996)

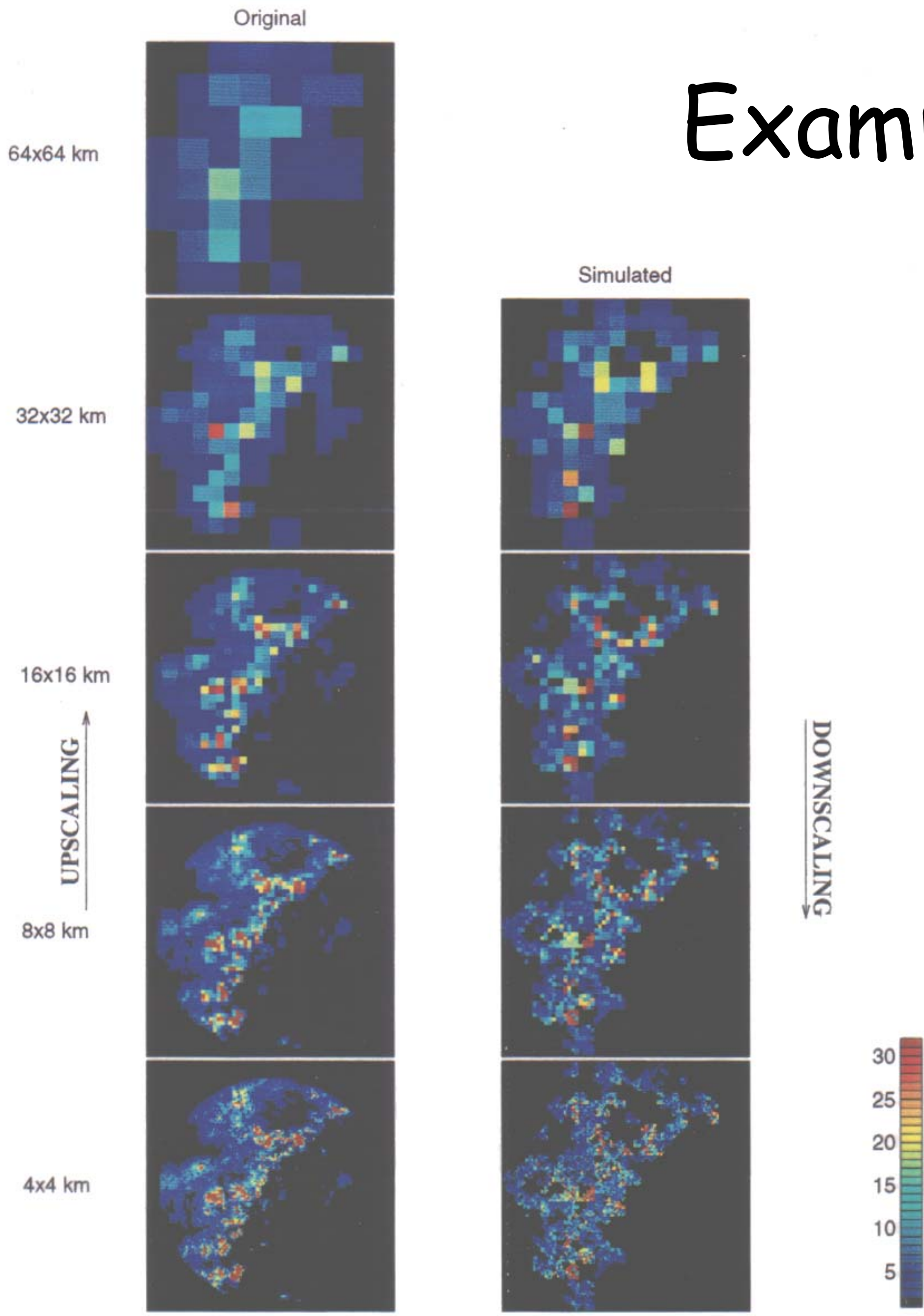
Example of downscaling



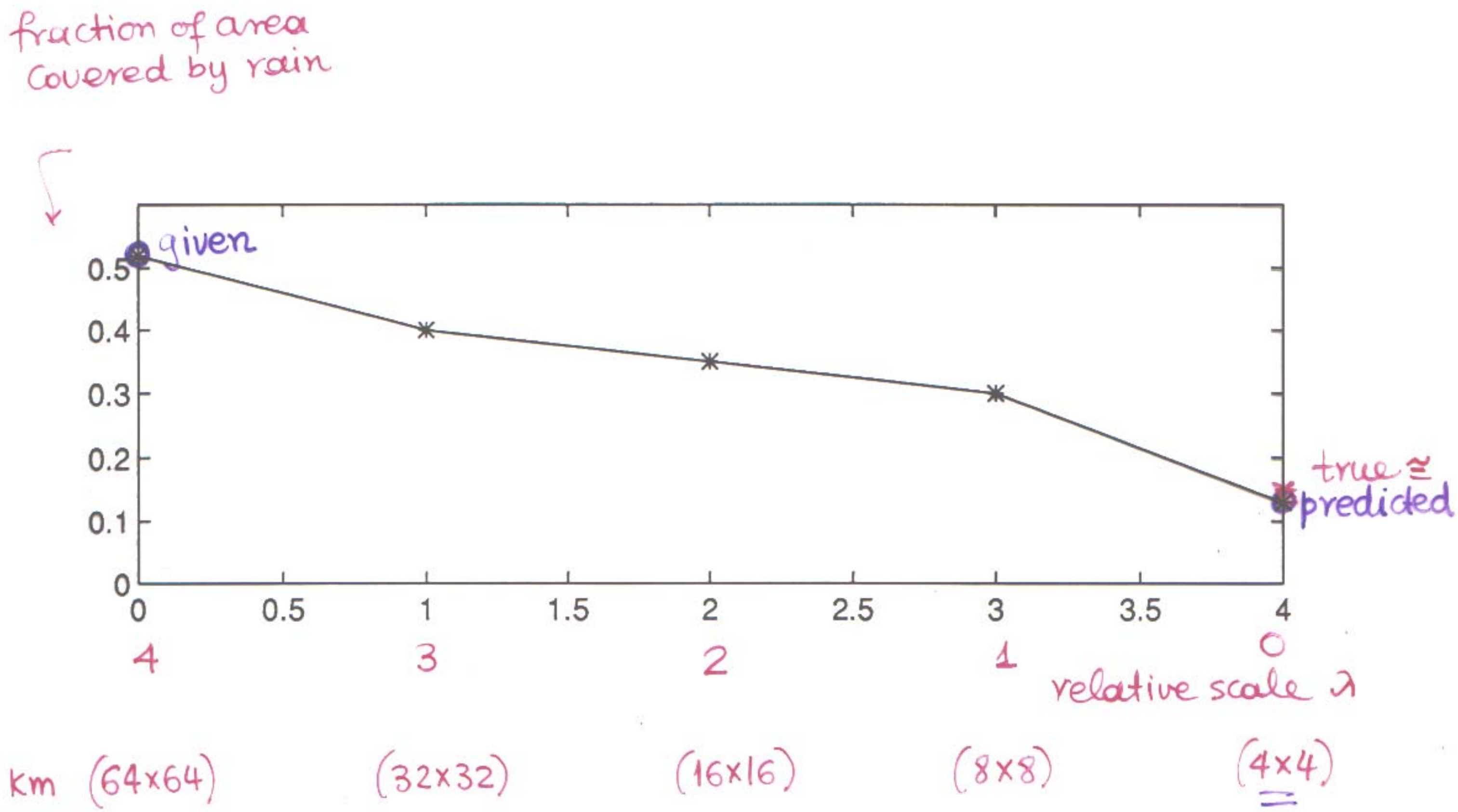
Example of downscaling



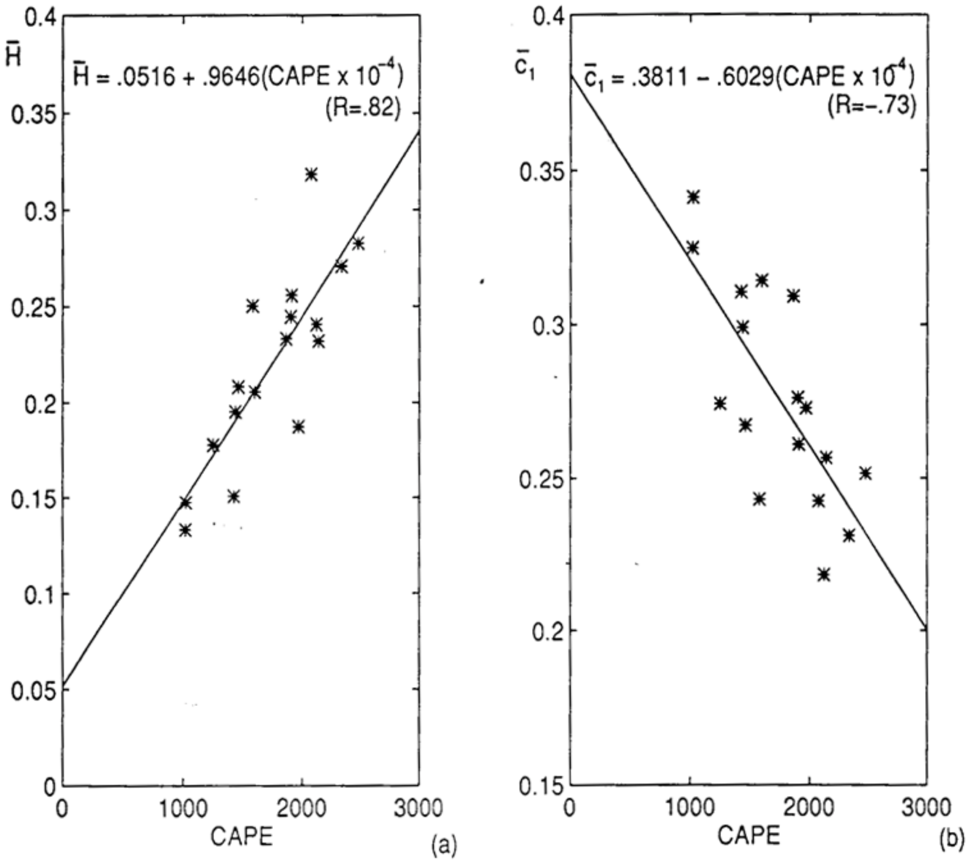
Example of downscaling



Performance of downscaling scheme



3. Relation of statistical parameters to physical observables



DEFINITION OF CAPE (m^2/sec^2)

$$CAPE = \int_{LFC}^{EL} g \cdot \left(\frac{\theta_c - \theta_{env}}{\theta_{env}} \right) dz$$

θ_c = potential T of an air parcel lifted from the surface to the level z

θ_{env} = potential T of the unsaturated environment at the same level

LFC = level of free convection

EL = equilibrium level

▷ CAPE is a measure of the potential instability

(See Perica and Foufoula-Georgiou, 1996)

Predictive downscaling

Given

- large scale mean (e.g. 64×64 km average rain)
- prestorm environmental conditions (CAPE)
- parameters of predictive equs (CAPE, $\bar{H}$), (CAPE, $\bar{q}$)

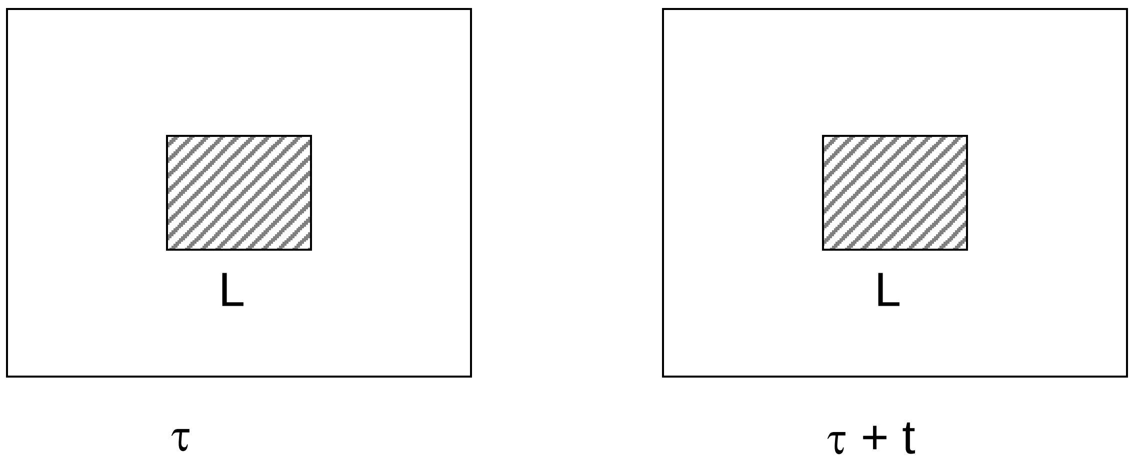
(IWT)

Find

- rainfall at **any** smaller scale

4. Space-time Downscaling

- ✓ Describe rainfall variability at several spatial and temporal scales
- ✓ Explore whether space-time scale invariance is present. Look at rainfall fields at times τ and $(\tau+t)$.

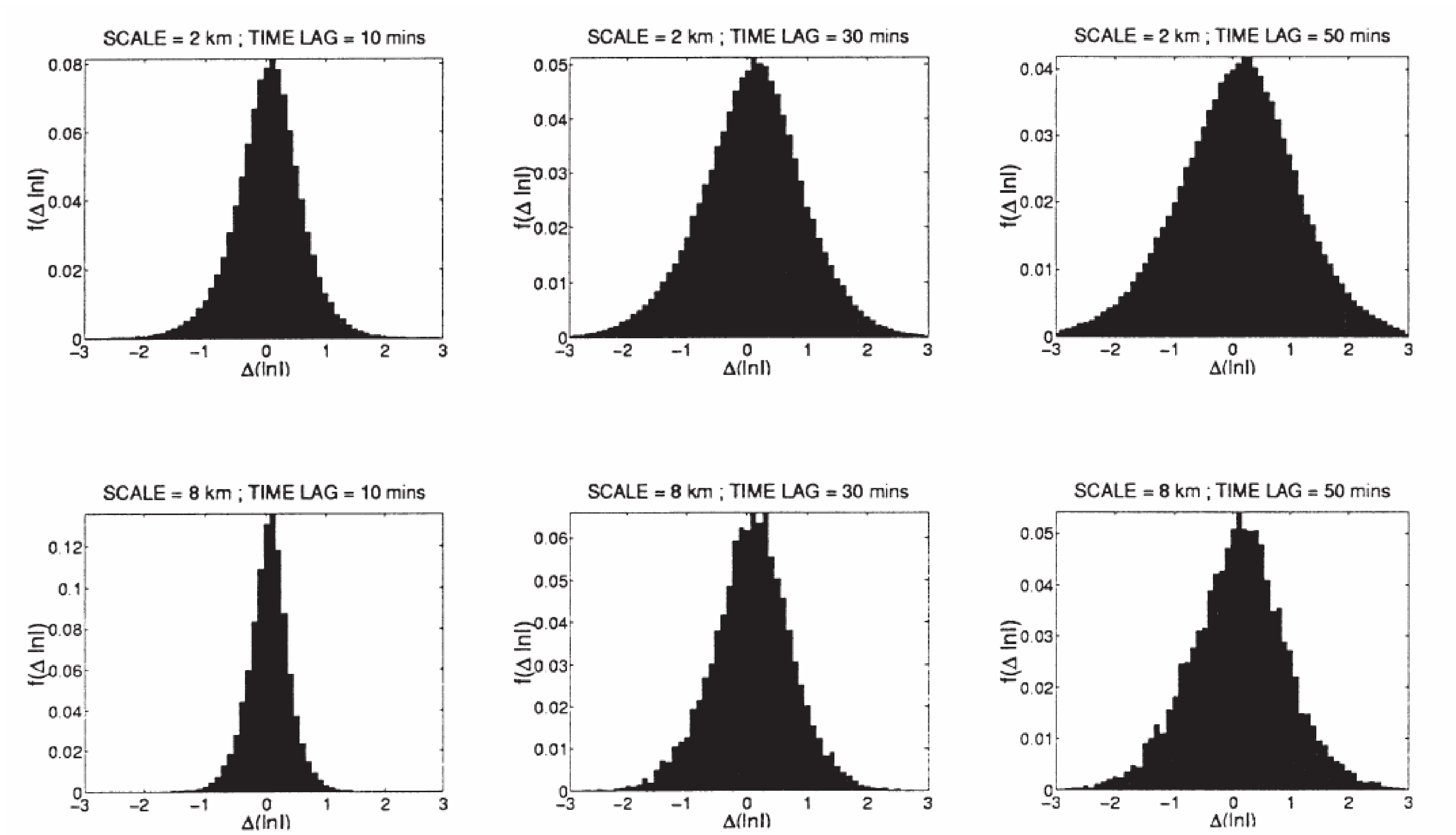


- ✓ Change L and t and compute statistics of evolving field

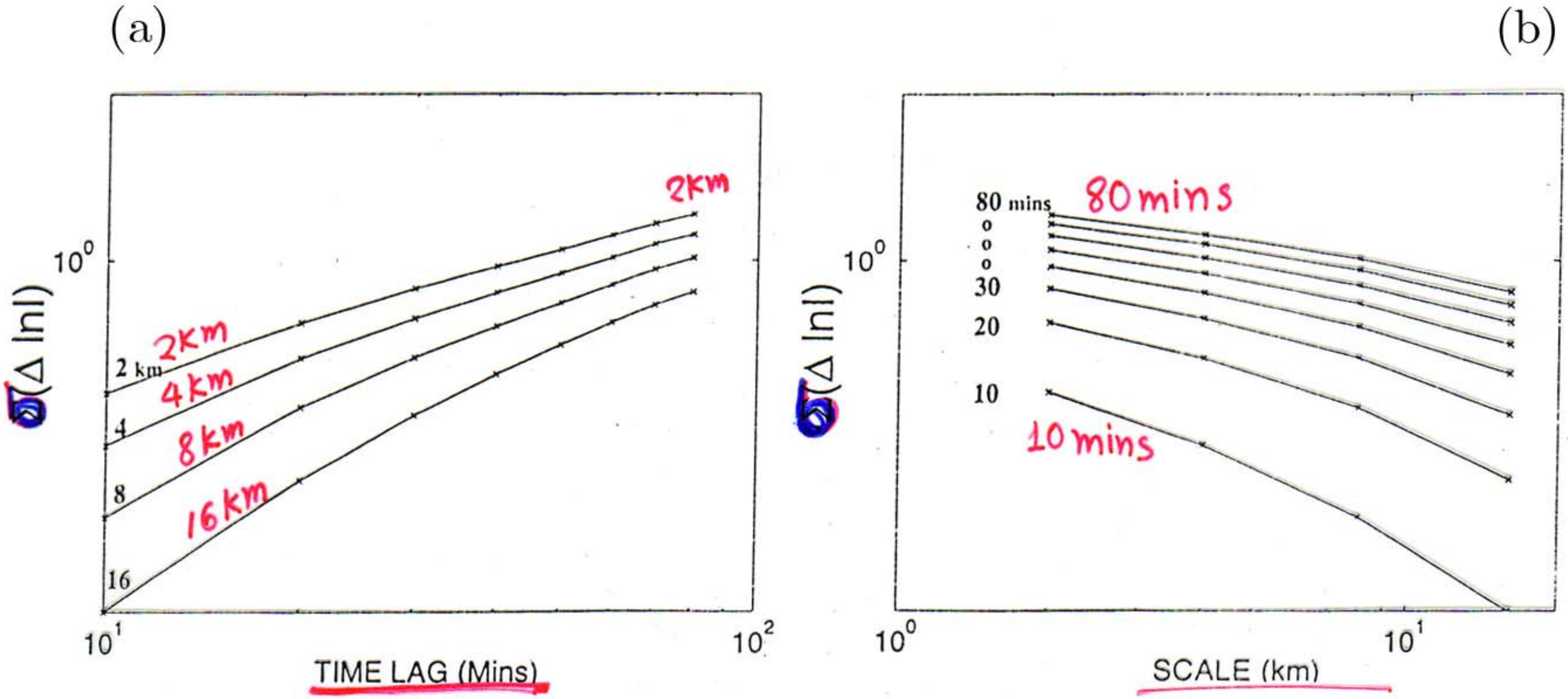
$$\Delta I(t, L) = I(\tau + t, L) - I(\tau, L)$$

$$\frac{\Delta I}{I}(t, L) = \frac{I(\tau + t, L) - I(\tau, L)}{\frac{1}{2}\left[I(\tau + t, L) + I(\tau, L)\right]} \longrightarrow \Delta \ln I(t, L)$$

PDFs of ΔlnI


SCALE = 2 km ; TIME LAG = 10 mins
SCALE = 2 km ; TIME LAG = 30 mins
SCALE = 2 km ; TIME LAG = 50 mins
SCALE = 8 km ; TIME LAG = 10 mins
SCALE = 8 km ; TIME LAG = 30 mins
SCALE = 8 km ; TIME LAG = 50 mins
f(Δ lnI)
Δ(lnI)

σ(Δ ln I) vs. Time Lag and vs. Scale



Space-time scaling

- ✓ Question: Is it possible to rescale space and time such that some scale-invariance is unraveled?

- ✓ Look for transformation that relate the dimensionless quantities (t_1/t_2) and (L_1/L_2)

- ✓ Possible only via transformation of the form $t \sim L^z$: "Dynamic scaling"

(See Venugopal, Foufoula-Georgiou and Sapozhnikov, 1996)

Variance of $\Delta \ln I(t,L)$

		Time Lag t (min)							
		10	**20**	**30**	**40**	**50**	**60**	**70**	**80**
L (km)	2	0.58	0.77	0.89	0.97	1.05	1.11	1.17	1.21
	4	0.47	0.67	0.79	0.87	0.95	1.01	1.07	1.12
	8	0.35	0.55	0.67	0.76	0.84	0.90	0.96	1.01
	16	0.23	0.40	0.53	0.63	0.71	0.77	0.83	0.88

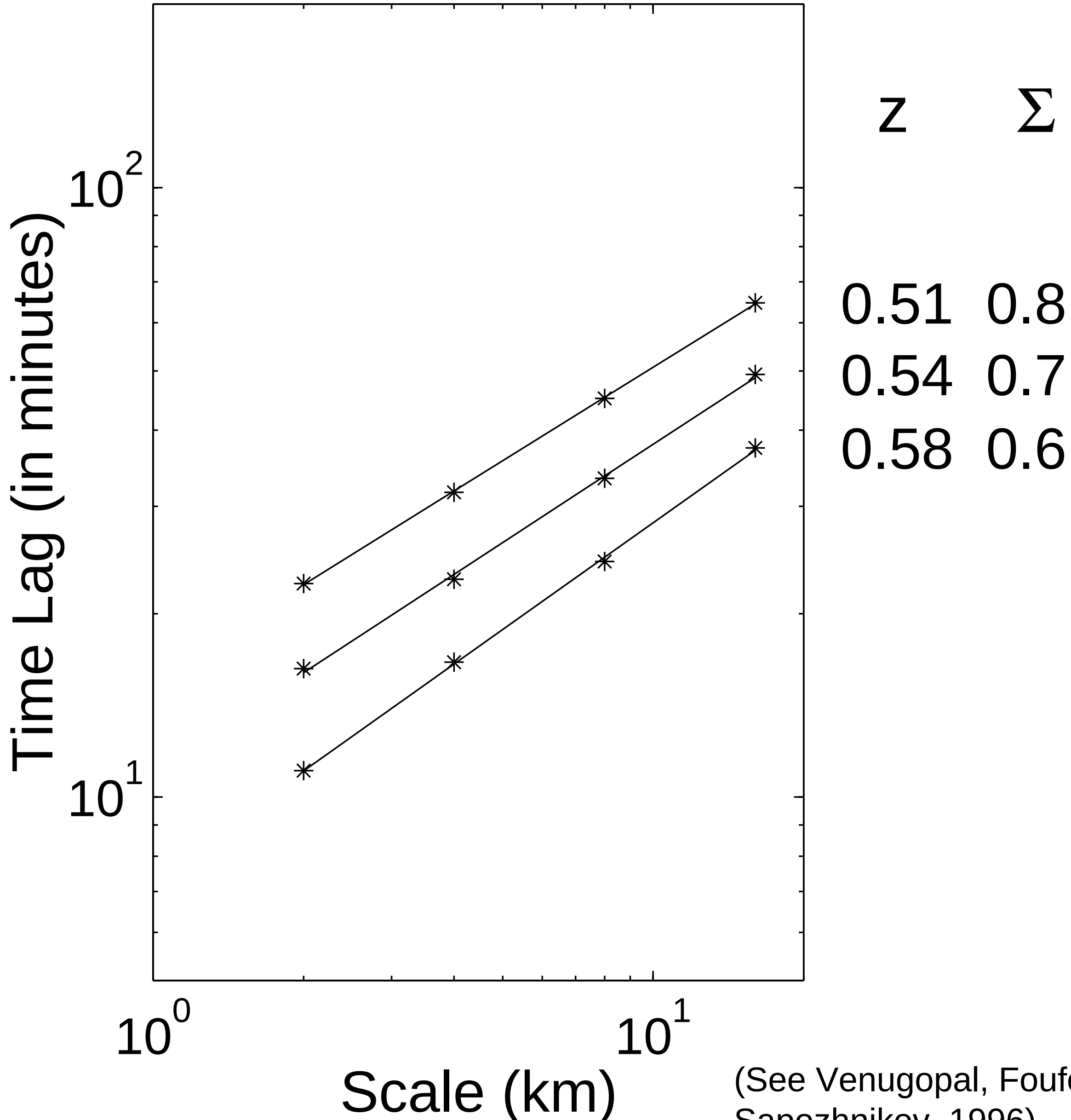
$$\Downarrow$$

Find (t,L) pairs for which $\mathrm{var}(\Delta \ln I) = \text{constant}$

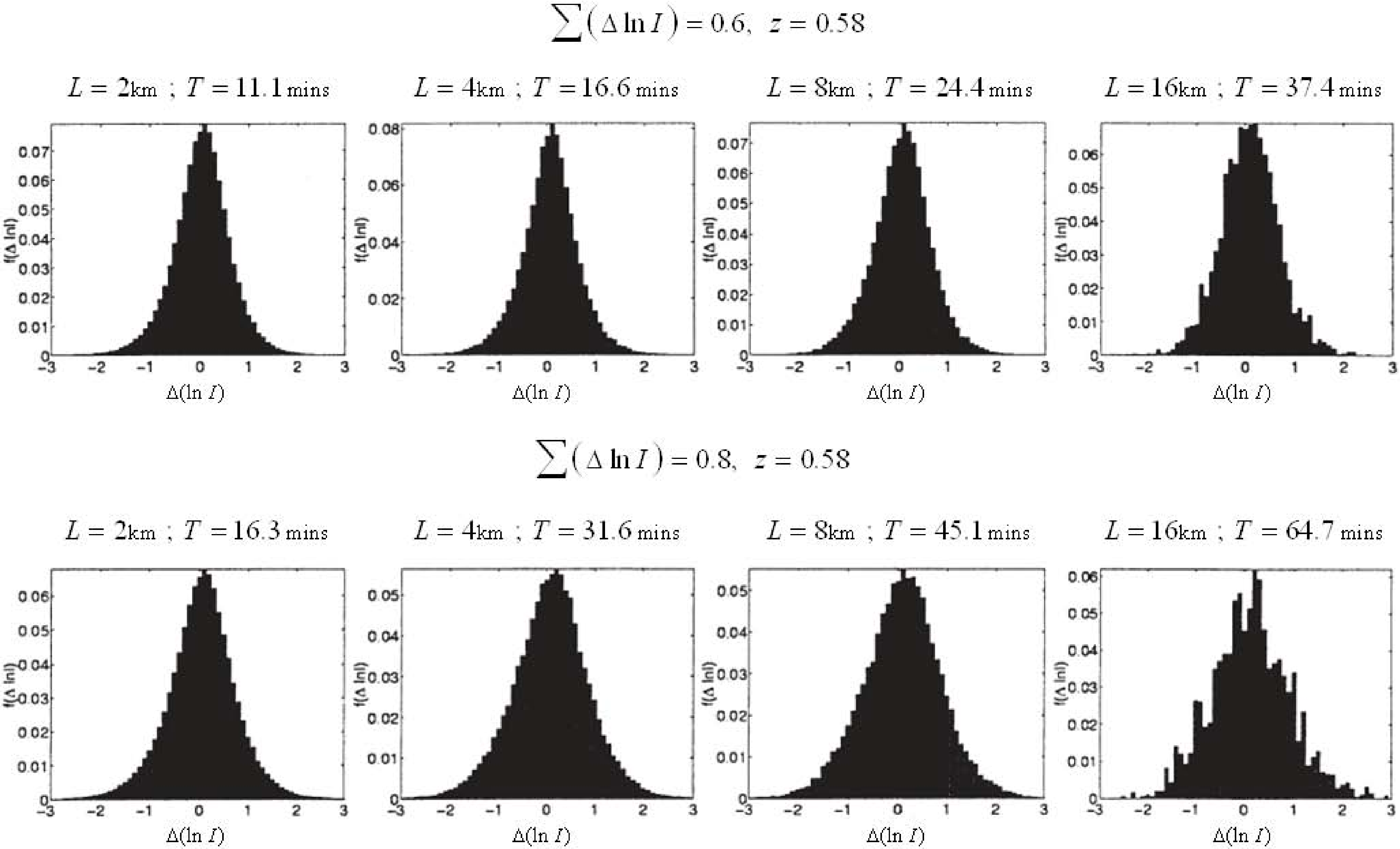
$$\Downarrow$$

		$\mathrm{var}(\Delta \ln I) = \sum(\Delta \ln I)$		
		0.6	**0.7**	**0.8**
L (km)	2	11.1	16.3	22.4
	4	16.6	22.8	31.6
	8	24.4	33.3	45.1
	16	37.4	49.4	64.7

Dec. 28, 1993 : Iso−Σ(Δ lnI) Lines



(See Venugopal, Foufoula-Georgiou and Sapozhnikov, 1996)



∑(Δ ln I) = 0.6, z = 0.58
L = 2km ; T = 11.1 mins
L = 4km ; T = 16.6 mins
L = 8km ; T = 24.4 mins
L = 16km ; T = 37.4 mins
f(Δ lnI)
Δ(ln I)
∑(Δ ln I) = 0.8, z = 0.58
L = 2km ; T = 16.3 mins
L = 4km ; T = 31.6 mins
L = 8km ; T = 45.1 mins
L = 16km ; T = 64.7 mins
f(Δ lnI)
Δ(ln I)

What do these values of z mean?

Consider for instance, $z = 0.6$,

Dynamic scaling implies

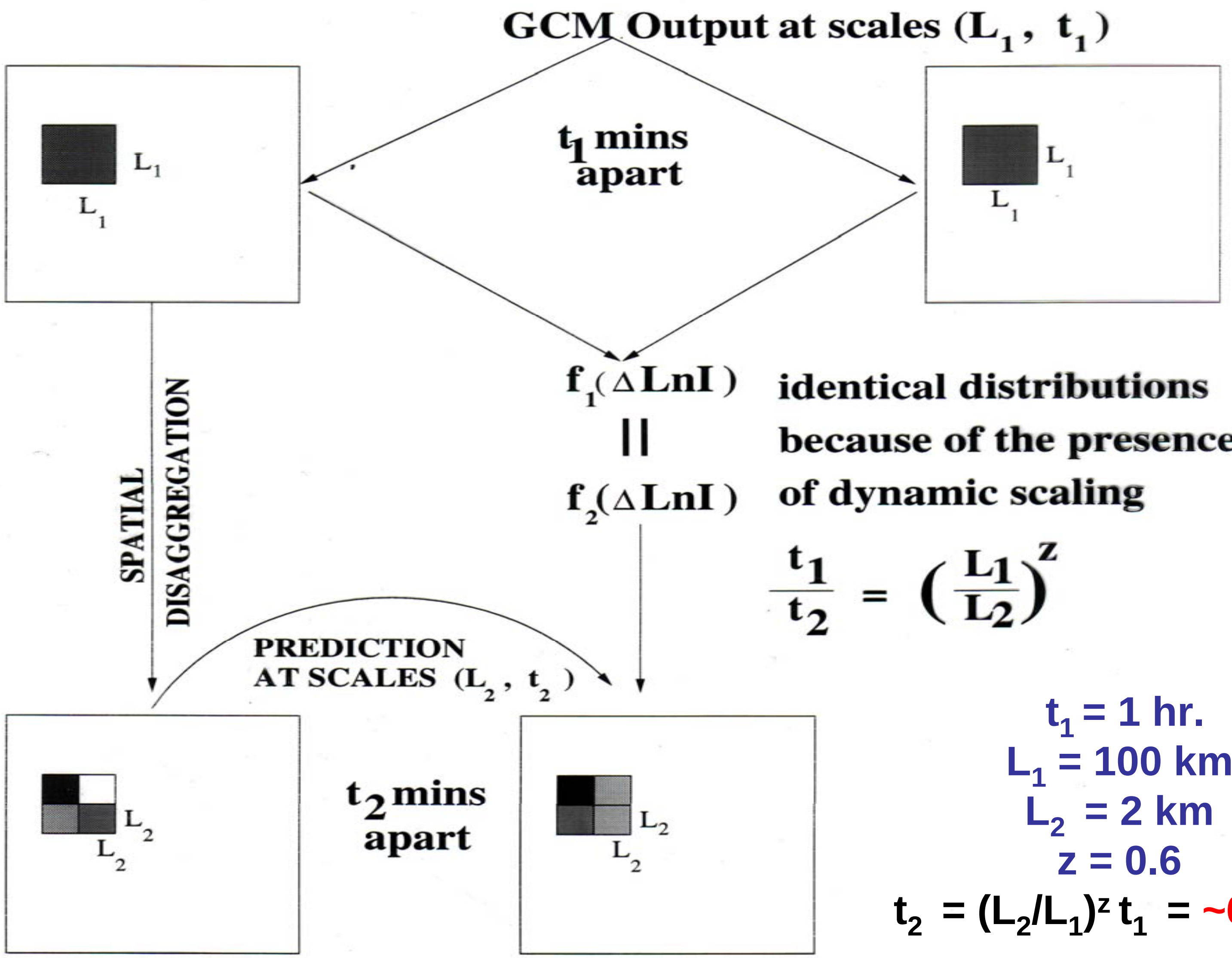
$$(t_1/t_2) = (L_1/L_2)^z$$

$\Longrightarrow$ A feature **eight times** smaller will evolve **3 times** faster than the larger feature.

since

$$t_2 = t_1 \left(\frac{16}{2}\right)^{0.6} \approx 3t_1$$

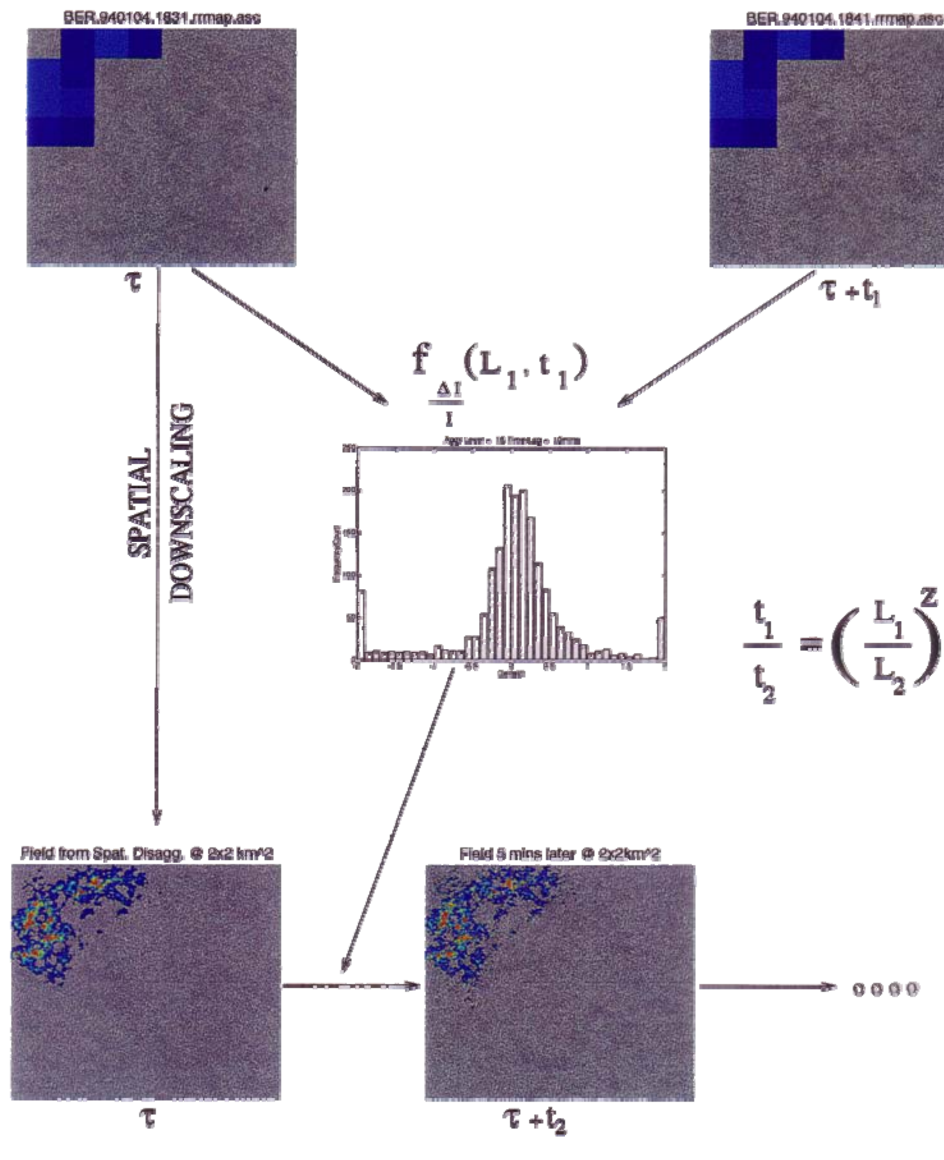
Schematic of space-time downscaling



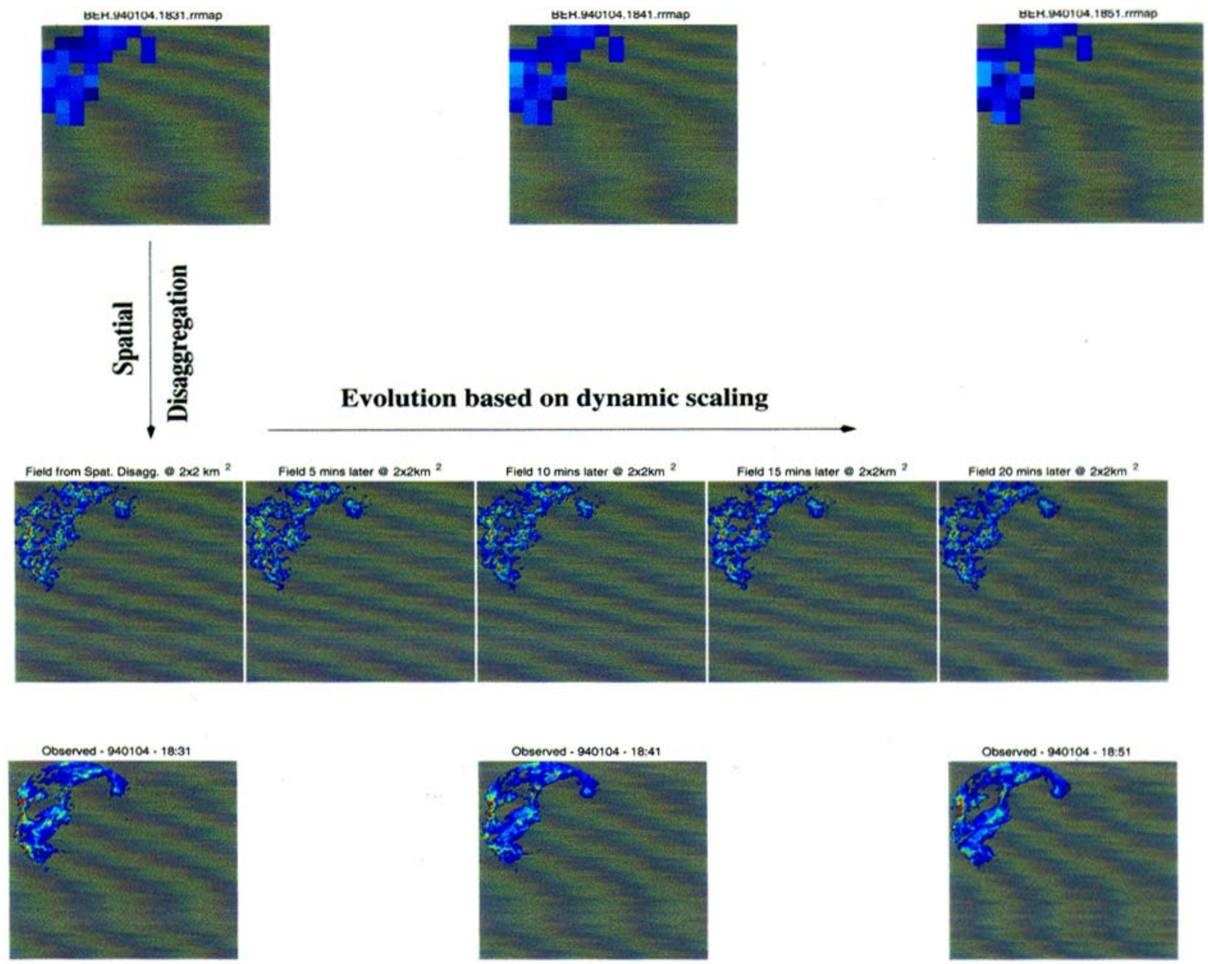
$$\frac{t_1}{t_2} = \left(\frac{L_1}{L_2}\right)^z$$

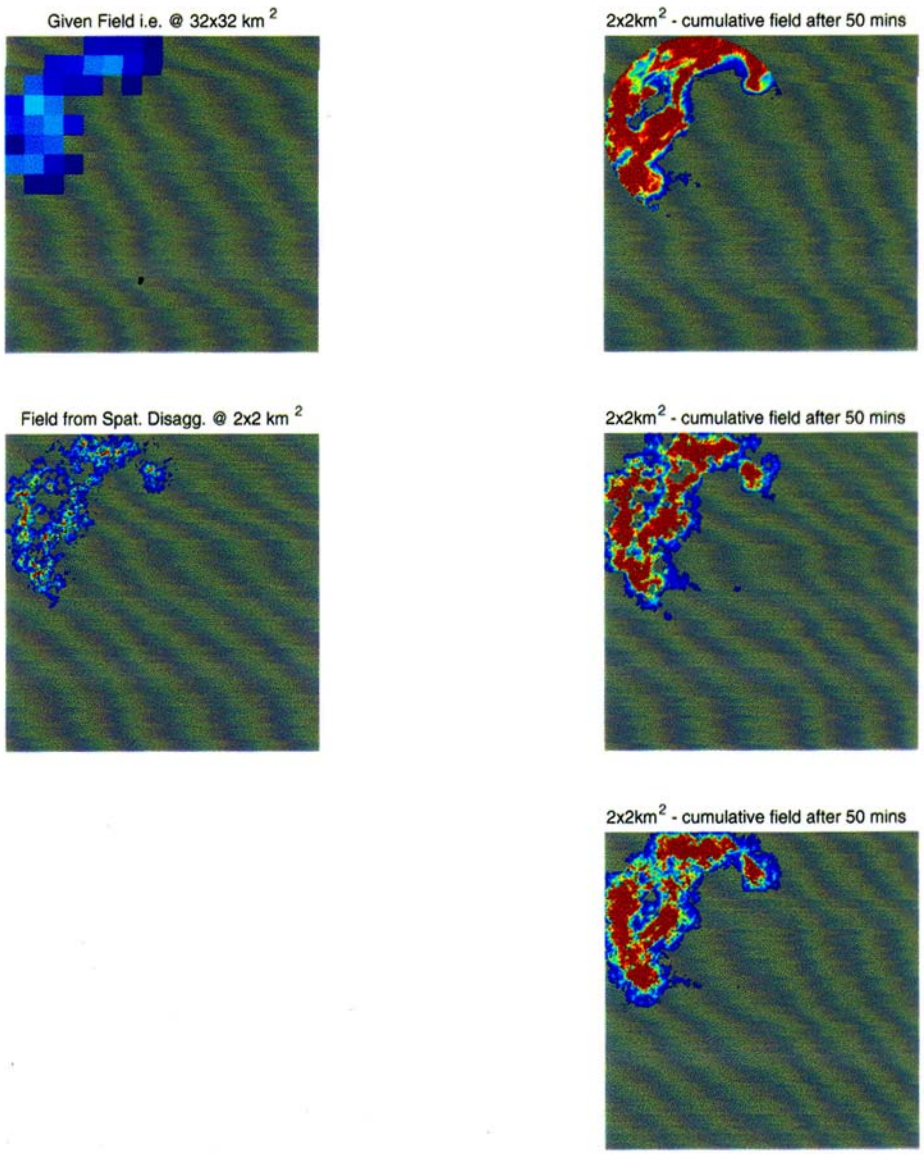
$t_1 = 1$ hr.
$L_1 = 100$ km
$L_2 = 2$ km
$z = 0.6$
$t_2 = (L_2/L_1)^z\, t_1 = \sim 6$ min.

Schematic of space-time downscaling



Space-time Downscaling preserves temporal persistence



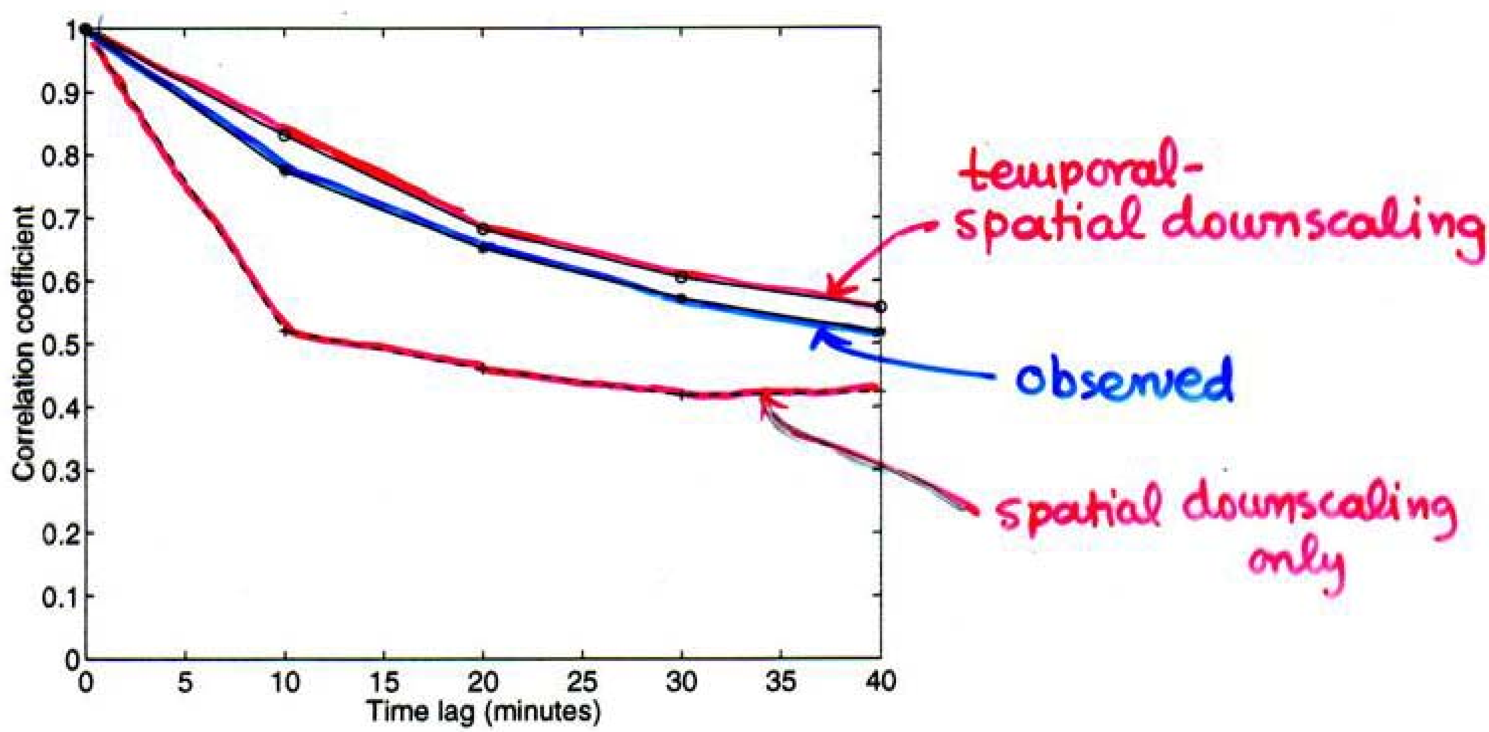


Observed

Accumulation of spatially downscaled field (every 10 minutes)

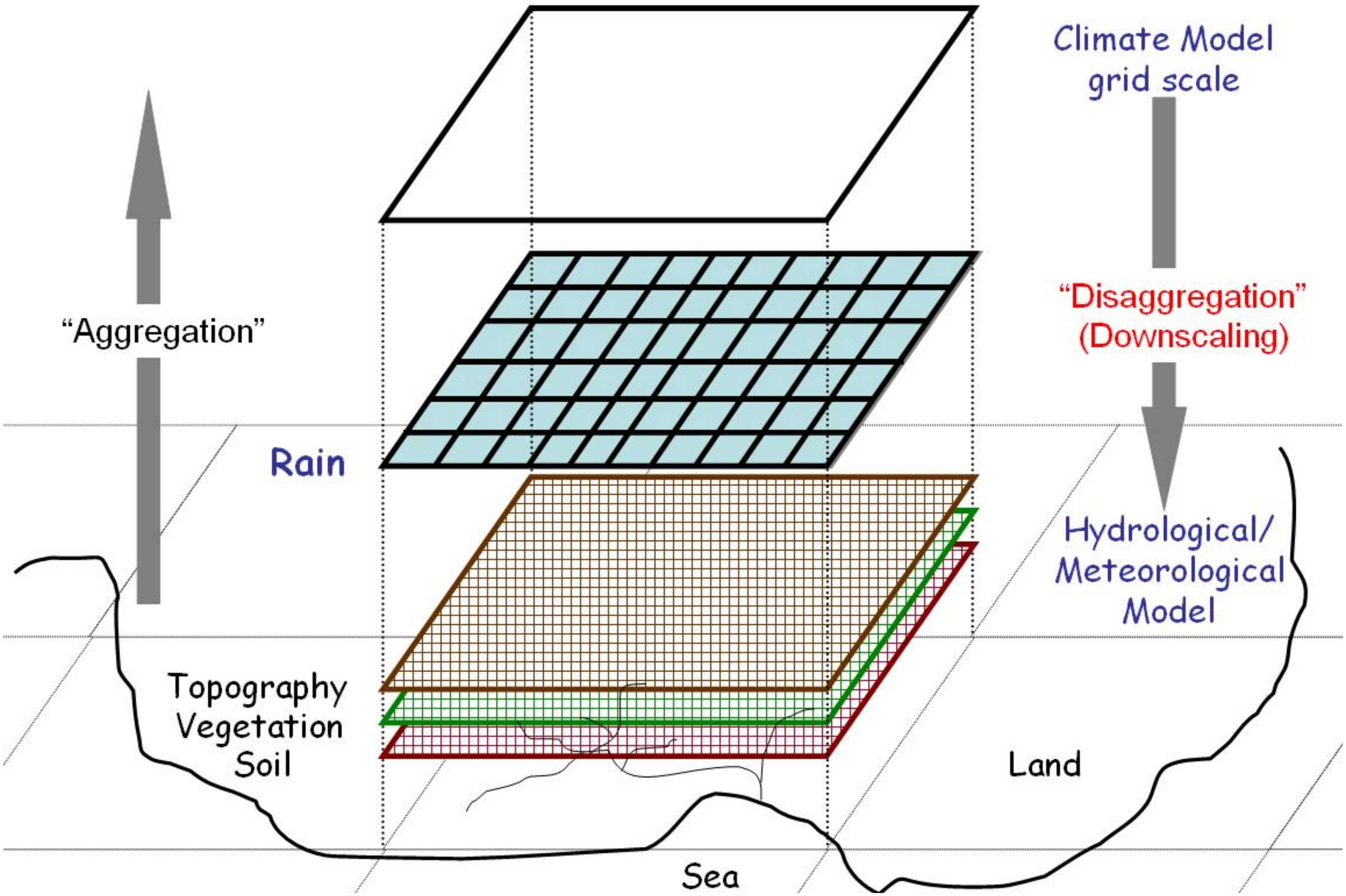
Space-time downscaling

(See Venugopal, Foufoula-Georgiou and Sapozhnikov, 1996)



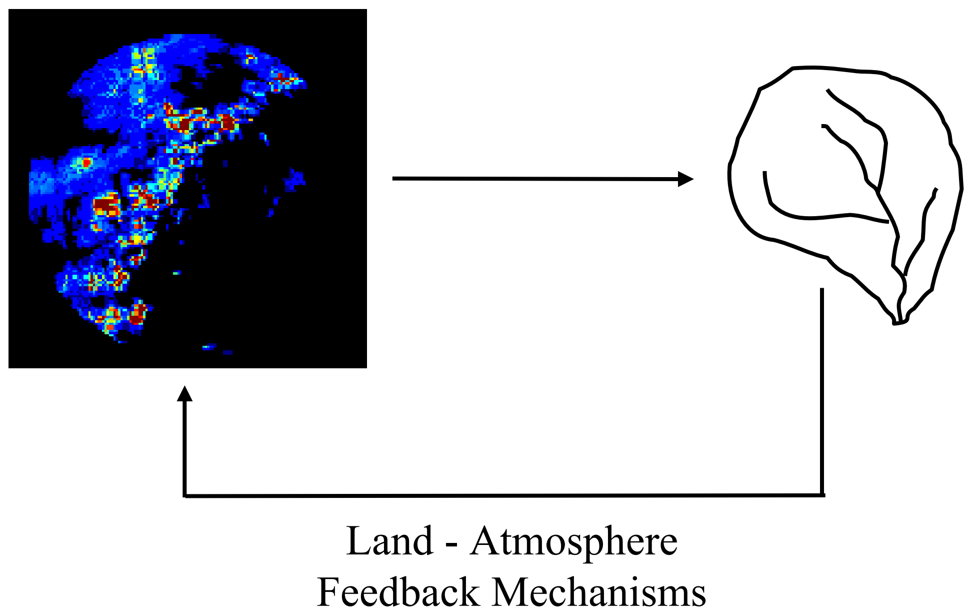
Correlation coefficient
Time lag (minutes)
temporal-spatial downscaling
observed
spatial downscaling only

5. Hydrological Applications



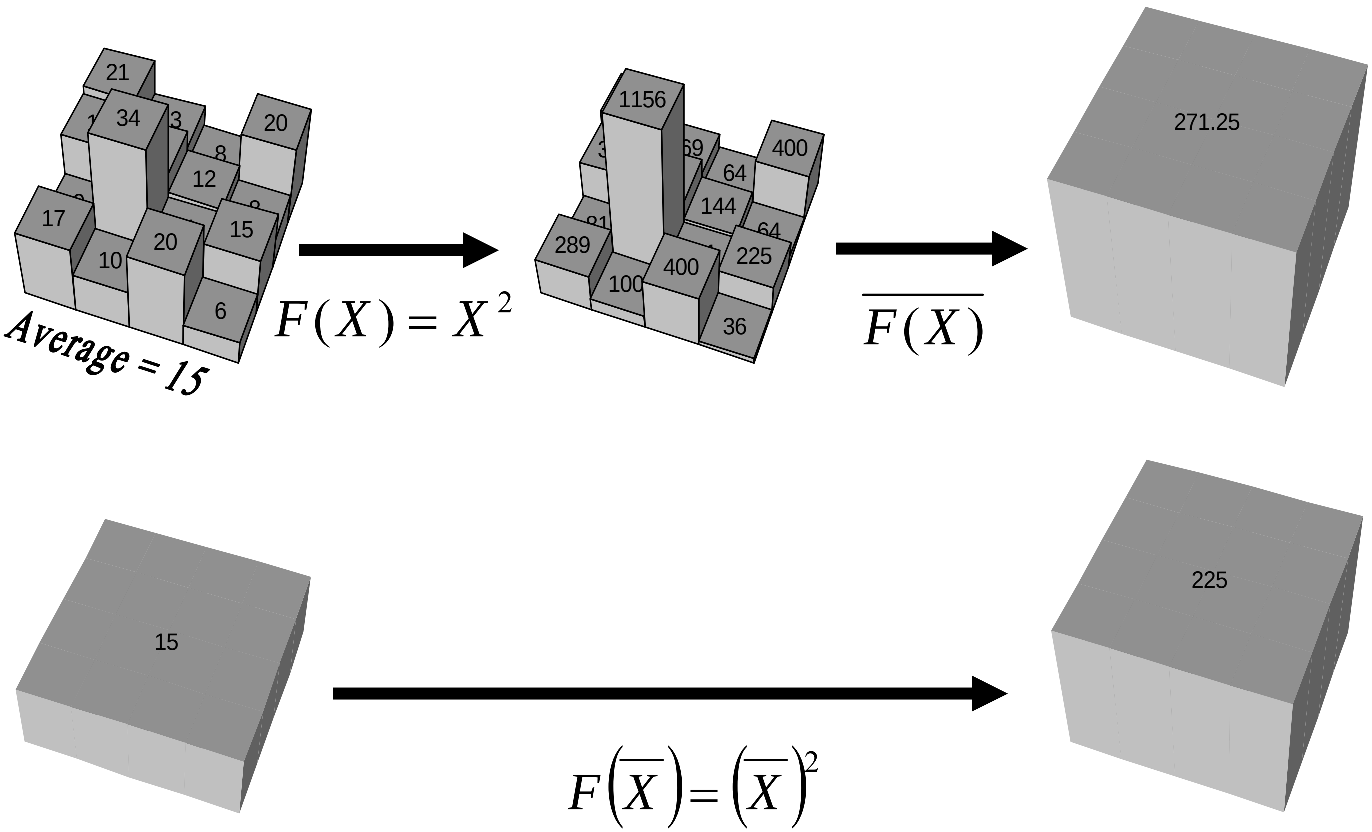
Effect of small-scale precipitation variability on runoff prediction

It is known that the land surface is not merely a static boundary to the atmosphere but is dynamically coupled to it.



Coupling between the land and atmosphere occurs at all scales and is nonlinear.

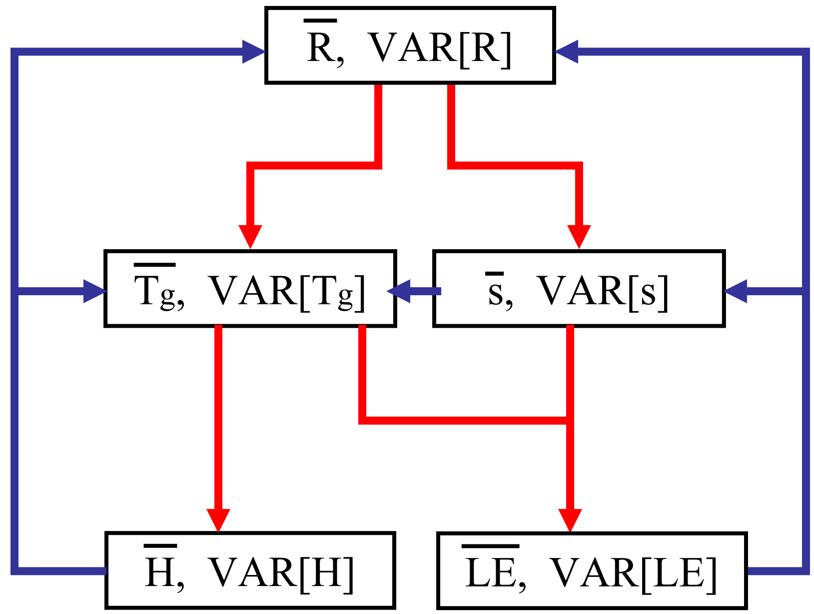
Nonlinear evolution of a variable



$$\overline{F(X)} = \frac{1}{N}\sum_{i=1}^{N} F(X_i) \neq F\left(\overline{X}\right)$$

- When subgrid-scale variability is introduced in the rainfall, it propagates through the nonlinear equations of the land-surface system to produce subgrid-scale variability in other variables of the water and energy budgets.

- Nonlinear feedbacks between the land-surface and the atmosphere further propagate this variability through the coupled land-atmosphere system.



Due to the nonlinearities of the physical equations and feedback mechanisms of the coupled land-atmosphere system, even the large-scale average values are effected (i.e., $\overline{F(X)} \neq F(\overline{X})$).

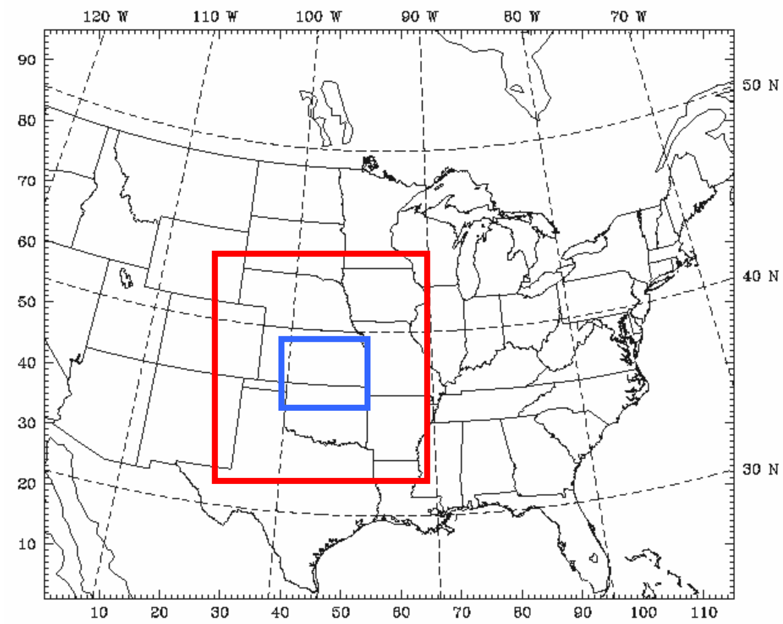
(See Nykanen and Foufoula-Georgiou, 2001)

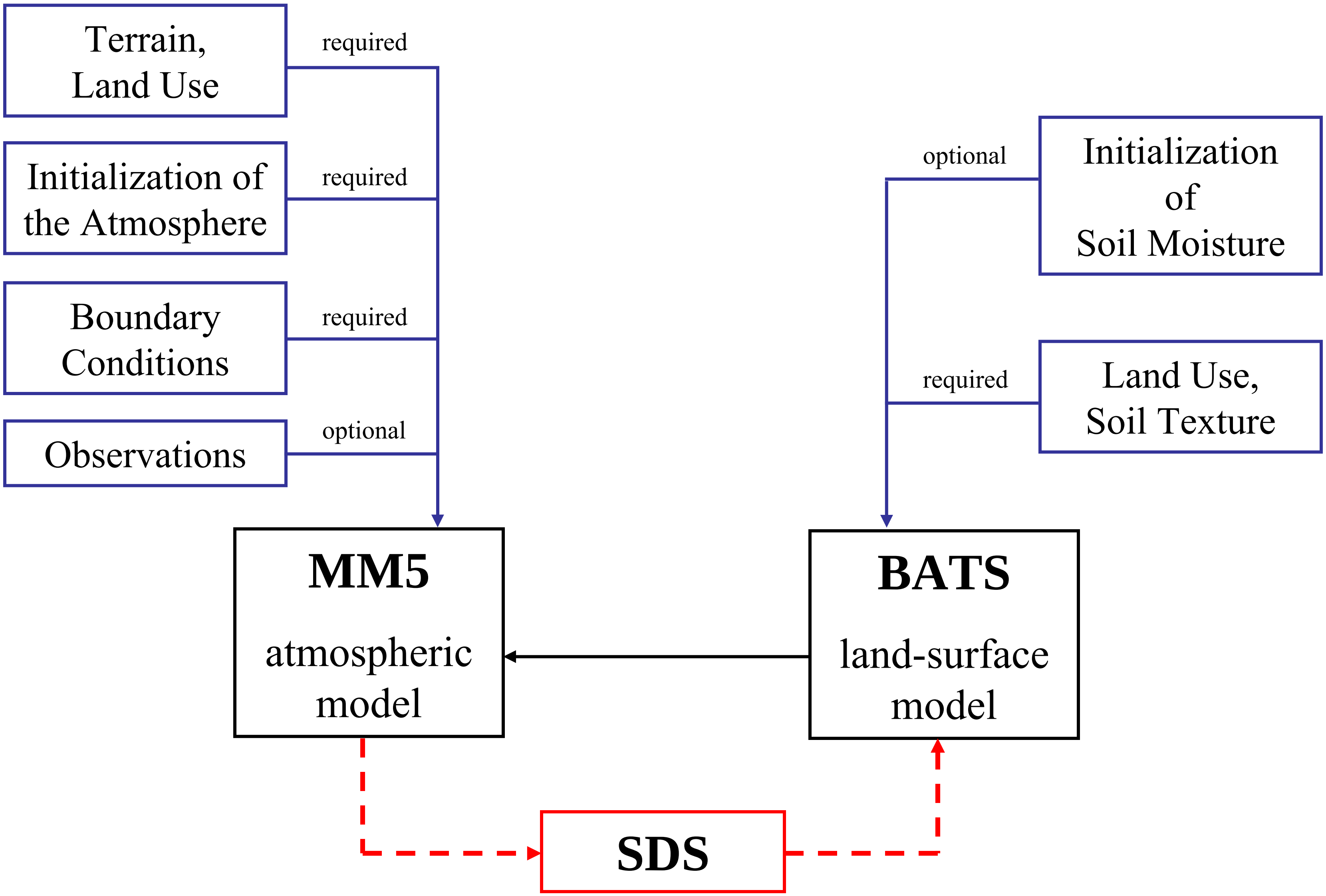
Methods to account for small-scale variability in coupled modeling

(1) Apply the model at a high resolution over the entire domain.

(2) Use nested modeling to increase the resolution over a specific area of interest.

(3) Use a dynamical/statistical approach to including small-scale rainfall variability and account for its nonlinear propagation through the coupled land-atmosphere system.





Statistical Downscaling
Scheme for Rainfall

(See Nykanen and Foufoula-Georgiou, 2001)

Rainfall Downscaling Scheme

(Perica and Foufoula-Georgiou, *JGR*, 1995)

→ It was found that for mesoscale convective storms, that normalized spatial rainfall fluctuations ($\xi = X'/X$) have a simple scaling behavior, i.e.,

$$\frac{\sigma_{\xi,\,L1}}{\sigma_{\xi,\,L2}} = \left(\frac{L_1}{L_2}\right)^H$$

→ It was found that H can be empirically predicted from the convective available potential energy (CAPE) ahead of the storm.

→ A methodology was developed to downscale the fields based on CAPE ⇒ H.

Simulation Experiment

•MM5: 36 km with 12 km nest

•BATS: 36 km with 3 km inside MM5's 12 km nest

•Rainfall Downscaling: 12 km → 3 km

Domain 1:

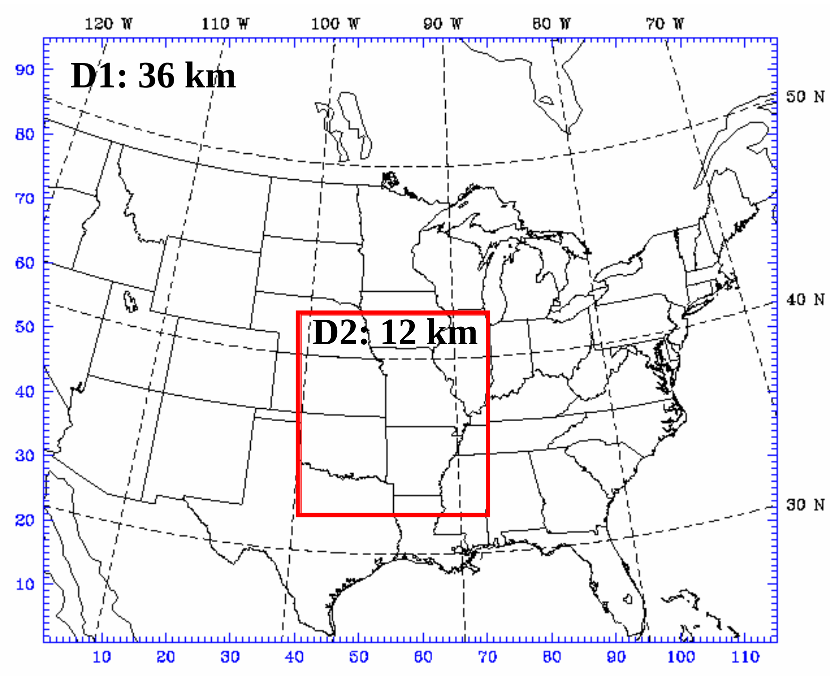
Run	MM5	BATS	Rainfall Downscaling
CTL	36 km	36 km	Off
SRV	36 km	36 km	Off

Domain 2:

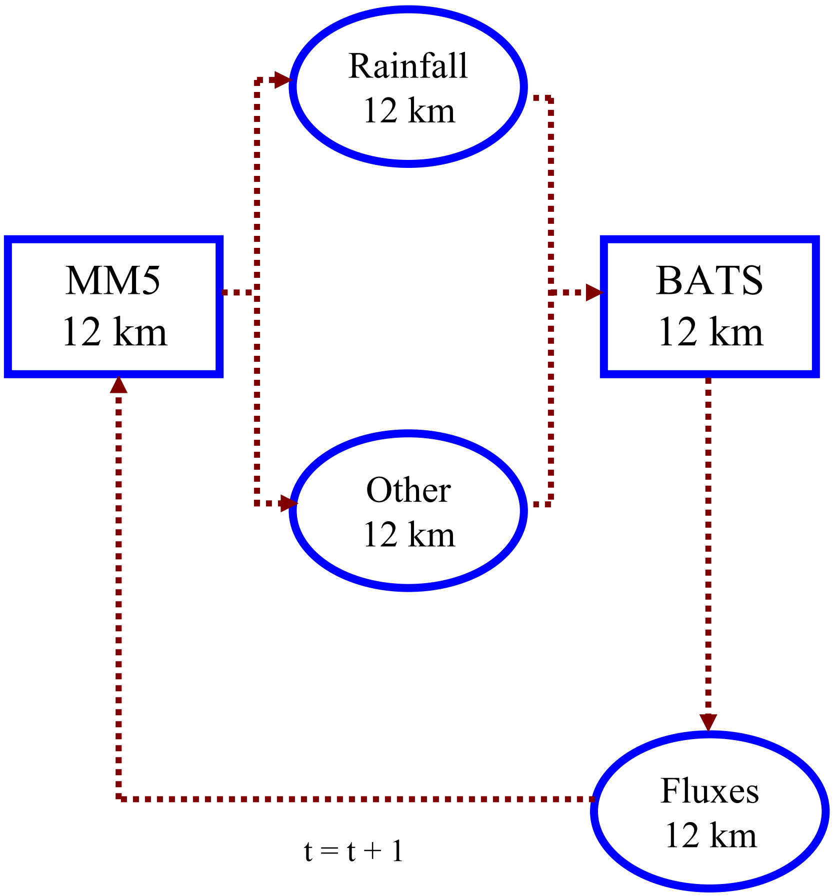
Run	MM5	BATS	Rainfall Downscaling
CTL	12 km	12 km	Off
SRV	12 km	3 km	12 km → 3 km

Case Study: July 4-5, 1995

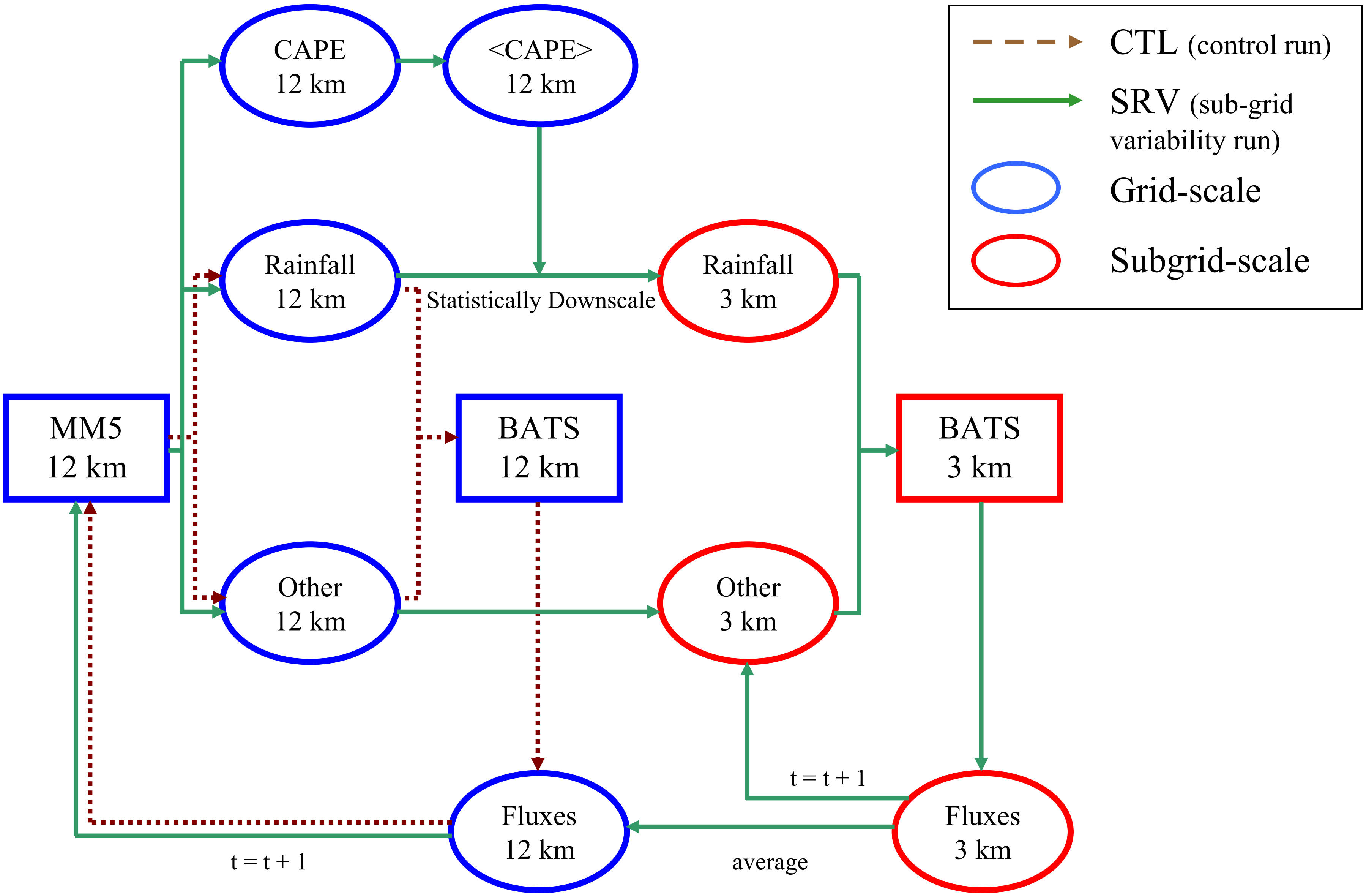
Initialization Time	July 4, 1995 12:00 UTC
Integration Time Step	D1: 90 sec., D2: 30 sec.
Simulation Length	48 hrs.
No. of Vertical Grid Elements	32
Horizontal Grid Resolution	D1: 36km, D2: 12 km
Initial and Lateral Boundary Conditions	NCEP Early Eta Model Analysis
Soil Moisture Initialization	Soil Hydrology Model (SHM) (via Penn State ESSC)
Land Cover, Soil Texture	USGS-EDC
Nesting Type	Two-way interactive
Cumulus Parameterization Scheme	Grell

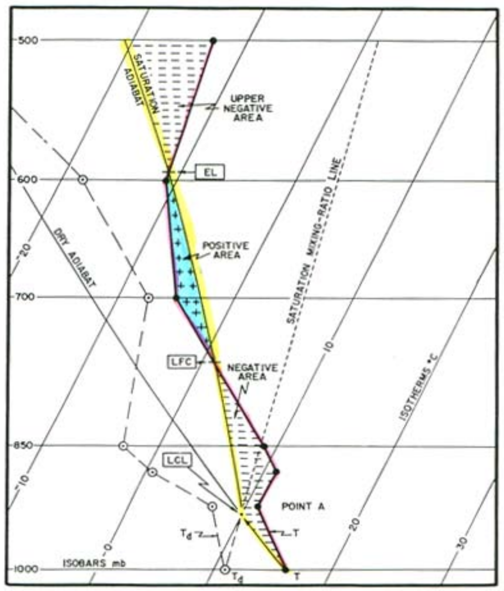


MM5/BATS



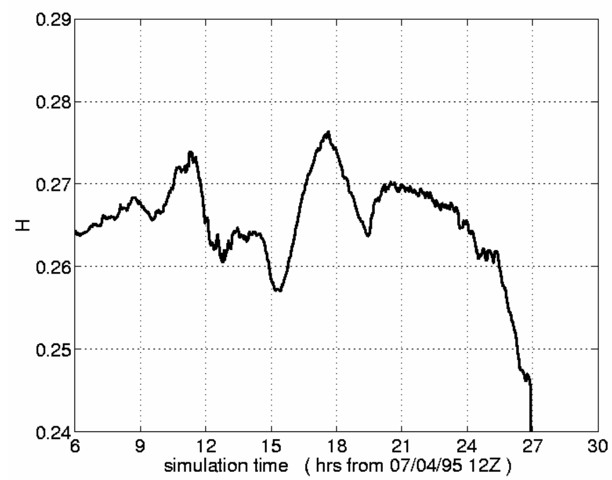
Subgrid-scale implementation of MM5/BATS



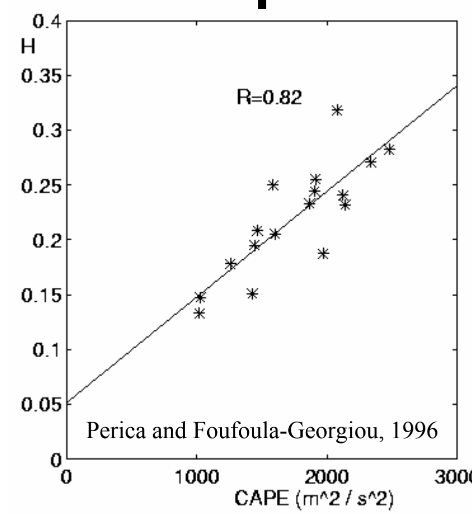


(adopted from AWS manual, 1979)

Yellow Line = Parcel
Pink Line = Environment
Positive Area = CAPE

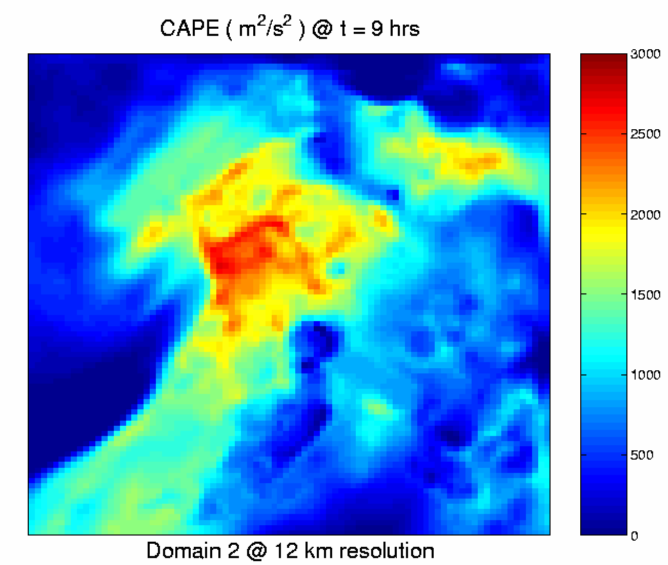


$$H = 0.052 + 0.965 < CAPE > \times 10^{-4}$$

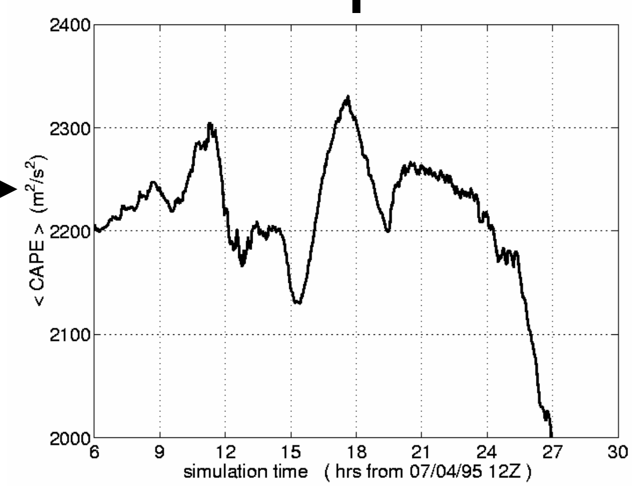


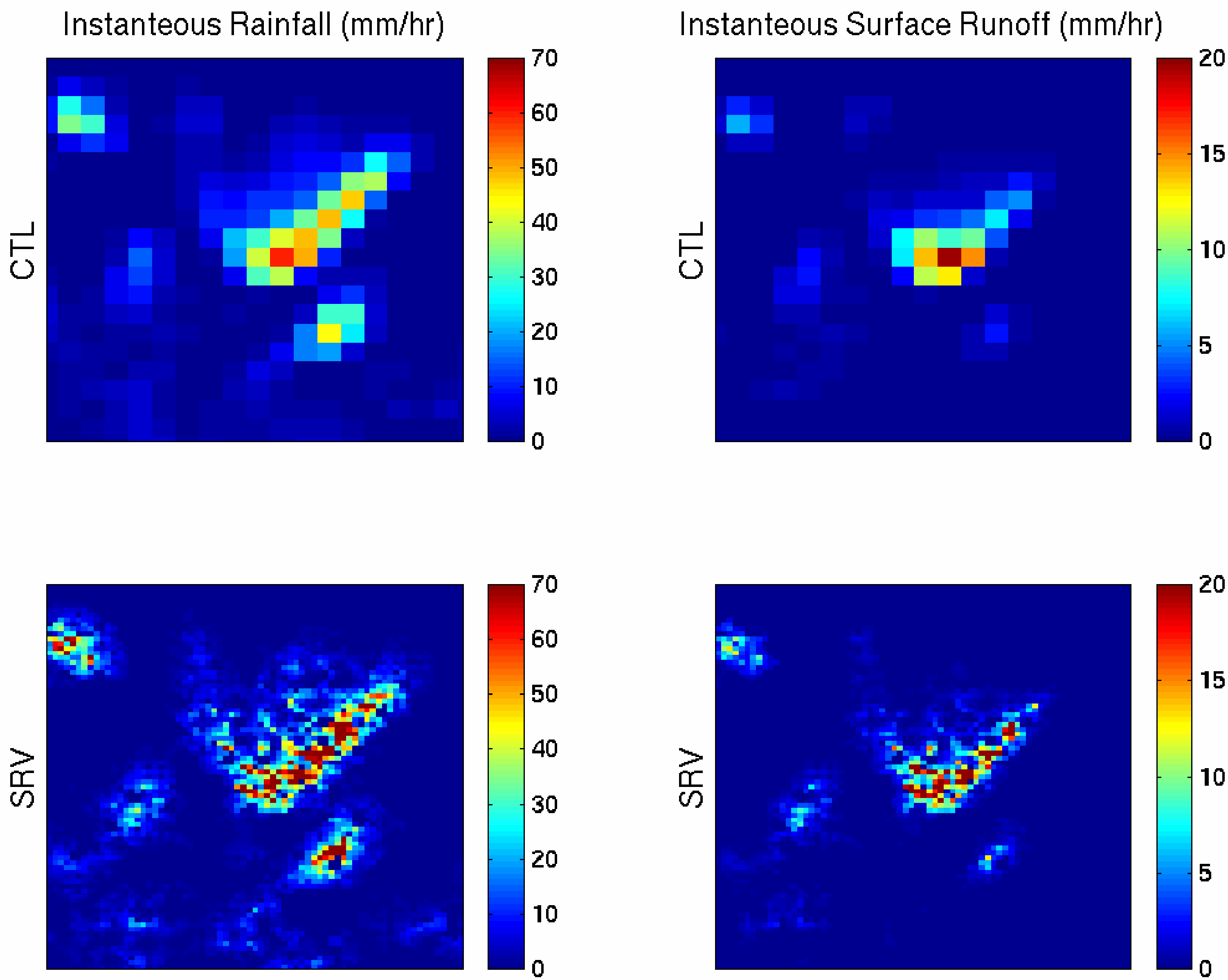
Perica and Foufoula-Georgiou, 1996

$$\frac{\sigma\xi, L_1}{\sigma\xi, L_2} = \left(\frac{L_1}{L_2}\right)^H$$



$$< CAPE > = \frac{1}{N_s} \sum_{i=1}^{N} CAPE_i \times I_{K_s, i}$$





sub-domain @ t = 11 hrs, 20 minutes (680 minutes) t = 27 hrs

at 12 km grid-scale

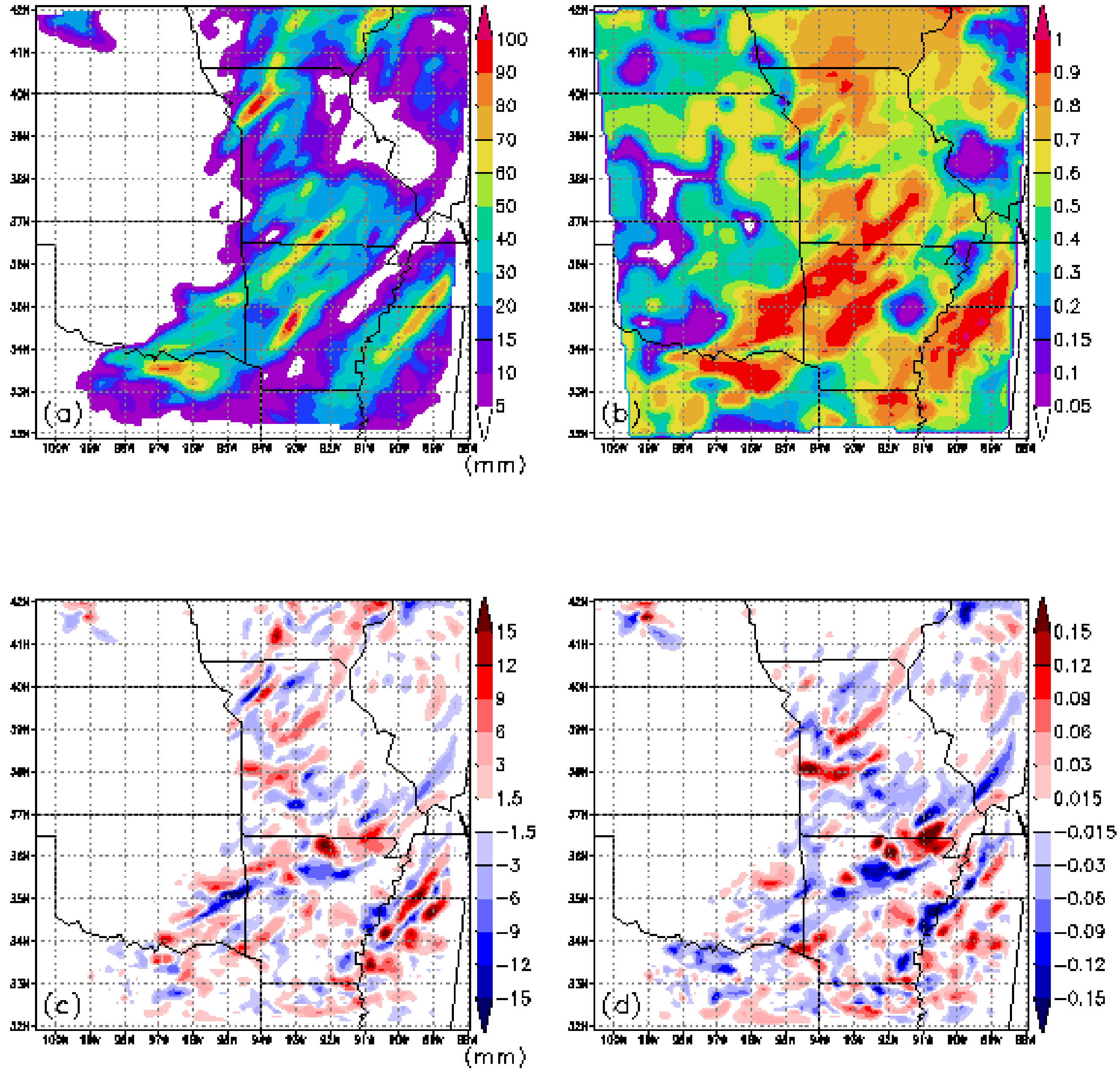
Total Accumulated Rainfall

Relative Soil Moisture in top 10 cm

CTL Run

Anomalies

(SRV - CTL)



t = 32 hrs

at 12 km grid-scale

Anomalies = SRV - CTL

Relative Soil Moisture in top 10 cm

(Su)

Surface Temperature

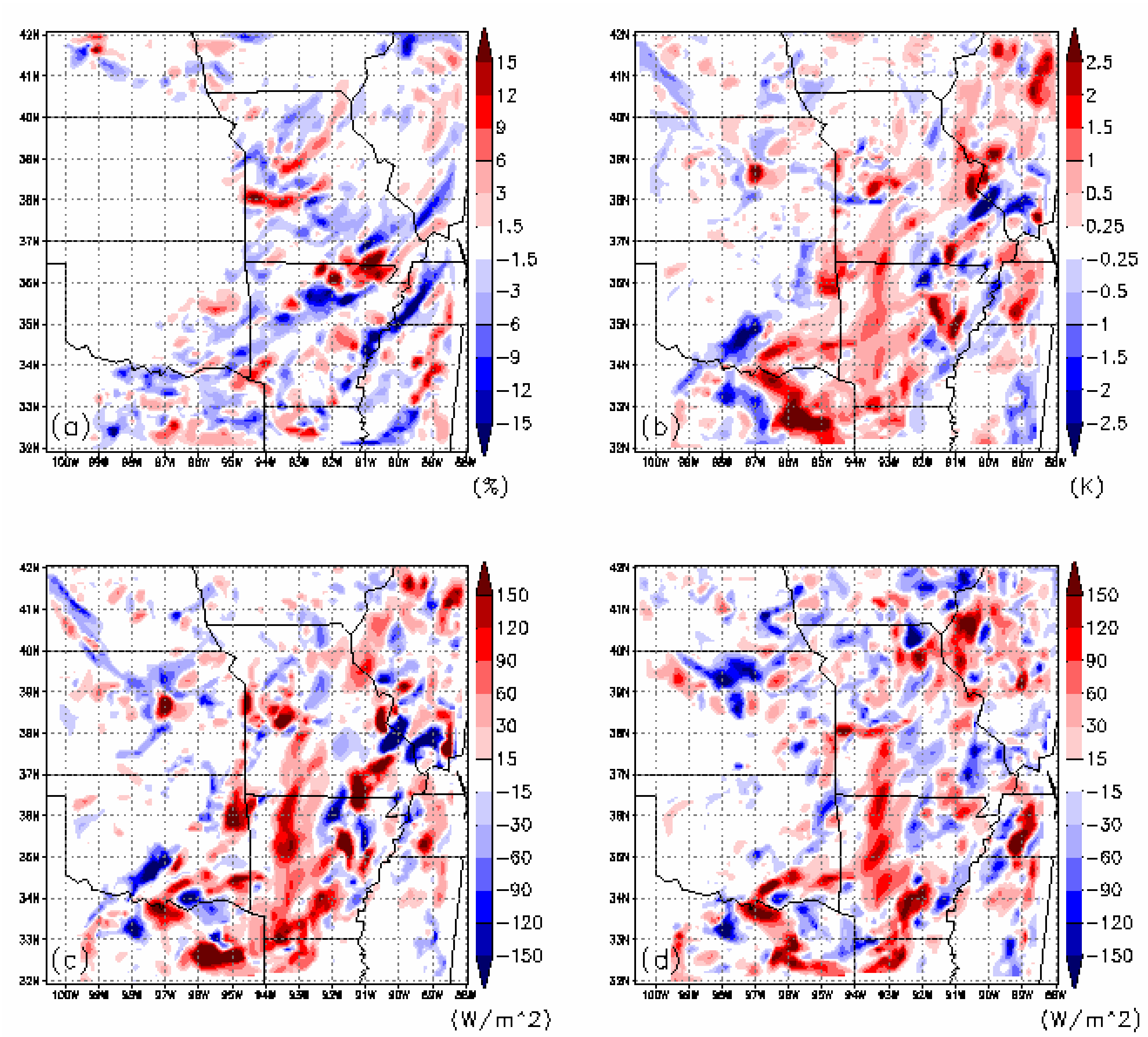
(TG)

Sensible Heat Flux from the surface

(HFX)

Latent Heat Flux from the surface

(QFX)



CONCLUSIONS

• Statistical downscaling schemes for spatial and space-time precipitation are efficient and work well over a range of scales

•The challenge is to relate the parameters of the statistical scheme to physical observables for real-time or predictive downscaling

•The effect of small-scale precipitation variability on runoff production, soil moisture, surface temperature and sensible and latent heat fluxes is considerable, calling for fine-scale modeling or scale-dependent empirical parameterizations

•For orographic regions other schemes must be considered

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