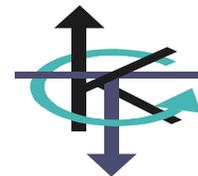


25~26 Feb. 2005 *Cherry Bud Workshop 2005 (Keio University)*



An approach to the extreme value distribution of non-stationary process

Hang CHOI & Jun KANDA

Institute of Environmental Studies
Graduate School of Frontier Sciences
The University of Tokyo

01 Theoretical Frameworks of EVA



- 1) Stationary Random Process (Sequence)
 - Distribution Ergodicity
 - (In)dependent and Identically Distributed random variables (**I.I.D. assumption**)
 - **strict stationarity**
 - * **Conventional approach**
- 2) Non-stationary Random Process (Sequence)
 - (In)dependent but non-identically Distributed random variables (**non-I.I.D. assumption**)
 - **weak stationarity, non-stationarity**
- 3) Ultimate (Asymptotic) and **penultimate** forms

1) I.I.D. random variable Approach



Ultimate form : Fisher-Tippett theorem (1928)

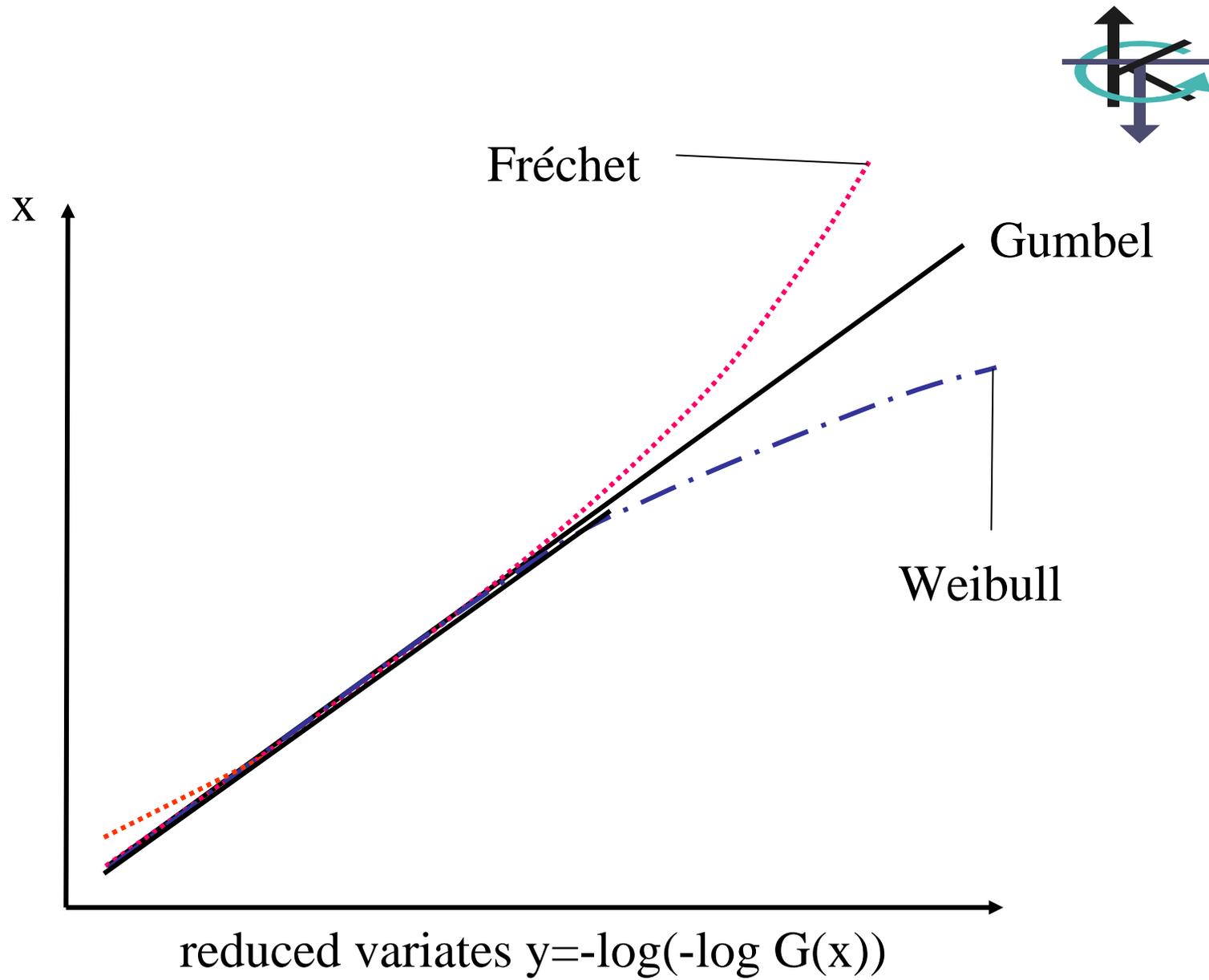
$$\underline{X_1, \dots, X_n} \in F(x), \quad Z_n = \max \{ X_1, \dots, X_n \}$$

$$\lim_{n \rightarrow +\infty} P \left(\frac{Z_n - a_n}{b_n} \leq x \right) = \lim_{n \rightarrow +\infty} \underline{F^n(a_n + b_n x)} = G(x) \in \mathbf{F}$$

$$\mathbf{F} = \{ \text{Gumbel, Fréchet, Weibull} \}$$



GEVD, GPD, POT-GPD + MLM, PWM, MOM etc.



2) non-I.I.D. random variable Approach

$$\underline{X_1 \in F_1(x), K, X_n \in F_n(x), Z_n = \max \{ X_1, K, X_n \}}$$

$$\lim_{n \rightarrow +\infty} P \left(\frac{Z_n - c_n}{d_n} \leq x \right) = \lim_{n \rightarrow +\infty} \prod_{j=1}^n F_j(d_j + c_j x) = Q(x) \in \mathcal{S}$$

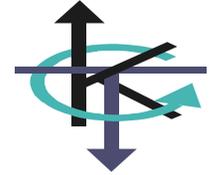
$$\mathcal{F} \subset \mathcal{S}$$

$$\mathcal{S} = \{ \text{Gumbel, Fréchet, Weibull, \dots} \}$$

The class of EVD for non-i.i.d. case is much larger.

* Falk *et al.*, *Laws of Small Numbers: Extremes and Rare Events*, Birkhäuser, 1994

3) Ultimate / penultimate form and finite epoch T in engineering practice



In engineering practice, the epoch of interest, T is finite. e.g. *annual* maximum value, *monthly* maximum value and maximum/minimum pressure coefficients in *10min* etc.

As such, the number of independent random variables m in the epoch T becomes a finite integer, i.e. $m < \infty$, and consequently, the theoretical framework for ultimate form is no longer available regardless *i.i.d.* or *non-i.i.d.* case.

Following discussions are restricted on the *penultimate d.f.* for the extremes of non-stationary random process *in a finite epoch T .*

02 Statement of the Problem

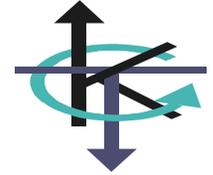


Let $x(t)$, $t \in \mathbb{R}^+ := [0, \infty)$ be the continuous observation record of a non-stationary continuous stochastic process $X(t)$ and assume that $X(t)$ is a mean square differentiable process and hold the following condition.

$$r(t, \tau) := E[X(t)X(t + \tau)] \Rightarrow r(t, \tau) \log \tau \rightarrow 0 \text{ as } \tau \rightarrow T$$

As such, how to estimate the extreme value distribution of $X(t)$ in an epoch $T < \infty$ from the continuous observation record $x(t)$?

03 Assumptions and Formulation



According to the conventional approach in wind engineering, let assume the non-stationary process $X(t)$ can be partitioned with a finite epoch T , in which the partitioned process $X_i(t), (i-1)T < t < iT$, can be assumed as an independent stationary random process, and define the d.f. $F_Z(x)$ as follows.

$$F_Z(x) = P(Z \leq x; Z := \sup X(t), t \in [0, T < \infty))$$

Then, by the Glivenko-Cantelli theorem and the block maxima approach

$$F_Z(x) = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n I_{(-\infty, x]}(Z_i := \sup X_i(t)) = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n P(Z_i \leq x)$$

where $I_c(x) = 1$ if $x \in c$ else 0

04 i.i.d. random sequence (EQRS)

approach of $P(Z_i \leq x)$

By partitioning the interval $[(i-1)T, iT)$ into finite subpartitions $[(j-1)h, jh)$, $1 \leq j \leq [T/h] = m_i$ in the manner of that

$$P(Z_i \leq x) = \prod_{j=1}^{m_i < \infty} P(Z_j^* \leq x; Z_j^* := \sup(X_i(t), t \in [(j-1)h, jh))) = F_{Z_i}^{m_i}(x)$$

the required d.f. $F_Z(x)$ can be defined as follows.

$$F_Z(x) := \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n F_{Z_i}^{m_i}(x)$$

If it is possible to assume that all $m_i \approx m$, then

$$F_Z(x) := \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n F_{Z_i}^m(x)$$

05 lower bound of $F_Z(x)$



From the inequality (geometric mean) < (arithmetic mean), a lower bound of $F_Z(x)$ can be defined as follows:

$$\hat{F}_Z(x) := \lim_{n \rightarrow \infty} \prod_{i=1}^n F_{Z_i}^{m/n}(x) < \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n F_{Z_i}^m(x) = F_Z(x)$$

06 alternative definition of $F_Z(x)$

$$\hat{F}_Z(x) := \left(\frac{1}{n} \sum_{i=1}^n F_{Z_i}(x) \right)^m = \bar{F}_Z^m(x)$$

This definition can be found easily in engineering applications and may be reasonable for the case of $F_{Z_1} ; \dots ; F_{Z_n}$.

07 Inequality of quantile functions



Let define quantile functions of each definition as follows.

$$Q(\alpha) := F_Z^{-1}(\alpha), \mathcal{Q}(\alpha) := F_Z^{\#-1}(\alpha), \hat{Q}(\alpha) := \hat{F}_Z^{-1}(\alpha)$$

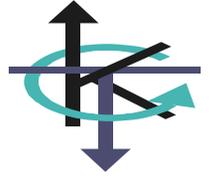
Then, by the inequality for the means and the comparison of the distribution of order statistics, i.e. $Z_{n:n}$ and $Z_{1:n}$,

$$Q(\alpha) \leq \mathcal{Q}(\alpha), \hat{Q}(\alpha) < \mathcal{Q}(\alpha) \text{ for all } \alpha \in (0,1)$$

$$\begin{cases} \hat{Q}(\alpha) < Q(\alpha) \rightarrow \mathcal{Q}(\alpha) & \text{for large } \alpha \\ Q(\alpha) < \hat{Q}(\alpha) < \mathcal{Q}(\alpha) & \text{for small } \alpha \end{cases}$$

Therefore, the alternative definition results in smaller variance of extremes.

Complement for the inequalities of quantile functions



$$\textcircled{1} \quad Z_{n:n} \sim \prod_{i=1}^n F_i^m, \quad \overset{\circ}{Z}_{n:n} \sim \left(\prod_{i=1}^n F_i^{m/n} \right)^n = \prod_{i=1}^n F_i^m \Rightarrow Z_{n:n}(\alpha) = \overset{\circ}{Z}_{n:n}(\alpha)$$

$$\textcircled{2} \quad \overset{\circ}{Z}_{n:n} \sim \prod_{i=1}^n F_i^m, \quad \bar{Z}_{n:n} \sim \left(\frac{1}{n} \sum_{i=1}^n F_i \right)^{mn}, \quad \left(\prod_{i=1}^n F_i^{m/n} \right)^n < \left(\frac{1}{n} \sum_{i=1}^n F_i \right)^{mn} \Rightarrow \overset{\circ}{Z}_{n:n}(\alpha) > \bar{Z}_{n:n}(\alpha)$$

$$\textcircled{3} \quad Z_{1:n} \sim 1 - \prod_{i=1}^n (1 - F_i^m); \quad \sum_{i=1}^n F_i^m - o(F^{2m}), \quad \bar{Z}_{1:n} \sim 1 - (1 - \bar{F}^m)^n; \quad \frac{1}{n^{m-1}} \sum_{i=1}^n F_i^m - o(F^{2m}) \\ \Rightarrow Z_{1:n}(\alpha) < \bar{Z}_{1:n}(\alpha)$$

$$\textcircled{4} \quad Z_{1:n} \sim 1 - \prod_{i=1}^n (1 - F_i^m), \quad \overset{\circ}{Z}_{1:n} \sim 1 - \left(1 - \prod_{i=1}^n F_i^{m/n} \right)^n,$$

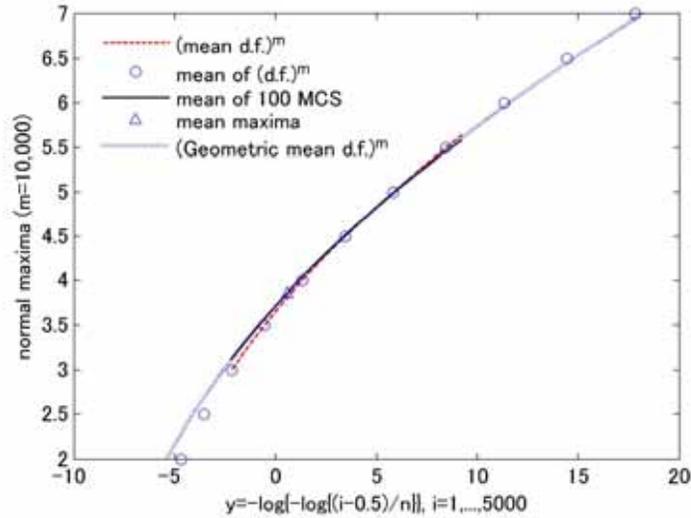
$$\prod_{i=1}^n (1 - F_i^m) < (1 - \bar{F}^m)^n < \left(1 - \prod_{i=1}^n F_i^{m/n} \right)^n \Rightarrow Z_{1:n}(\alpha) < \overset{\circ}{Z}_{1:n}(\alpha)$$

08 Numerical example $\bar{F}(x) = N(0,1)$

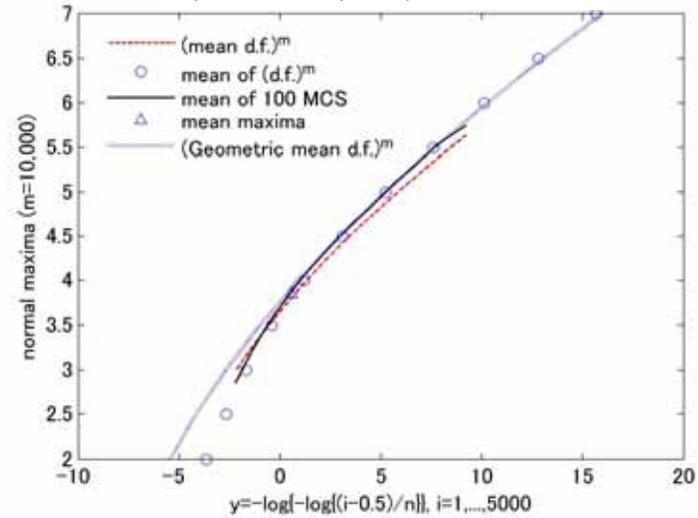
($m=10,000$, $n=5,000$, iteration=100)



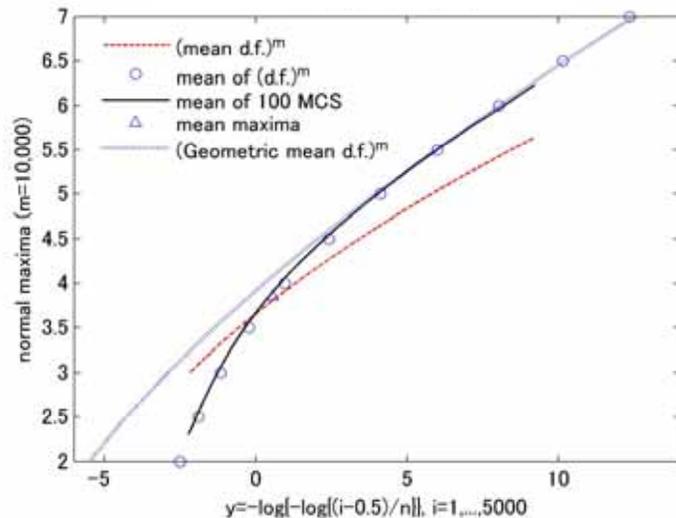
$X_i \sim N(0,1)$



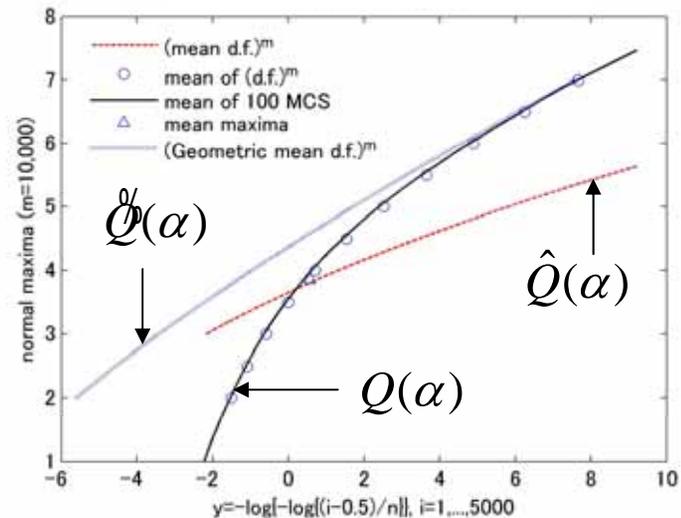
$X_i \sim N(0, \sigma_i), \sigma_i \sim N(1, 0.05)$



$X_i \sim N(0, \sigma_i), \sigma_i \sim N(1, 0.1)$



$X_i \sim N(0, \sigma_i), \sigma_i \sim N(1, 0.2)$



09 practical application:

Annual maximum wind speed in Japan



1) Observation records and Historical annual maximum wind speeds at 155 sites in Japan

Observation Records: JMA records (CSV format)

1961~1990 : 10 min average wind speed per 3 hours

1991~2002 : 10 min average wind speed per hour

Historical annual maximum wind speeds record:

1929~1999 : A historical annual max. wind speed data set
compiled by Ishihara *et al.*(2002)

2000~2002 : extracted from JMA records (CSV format)

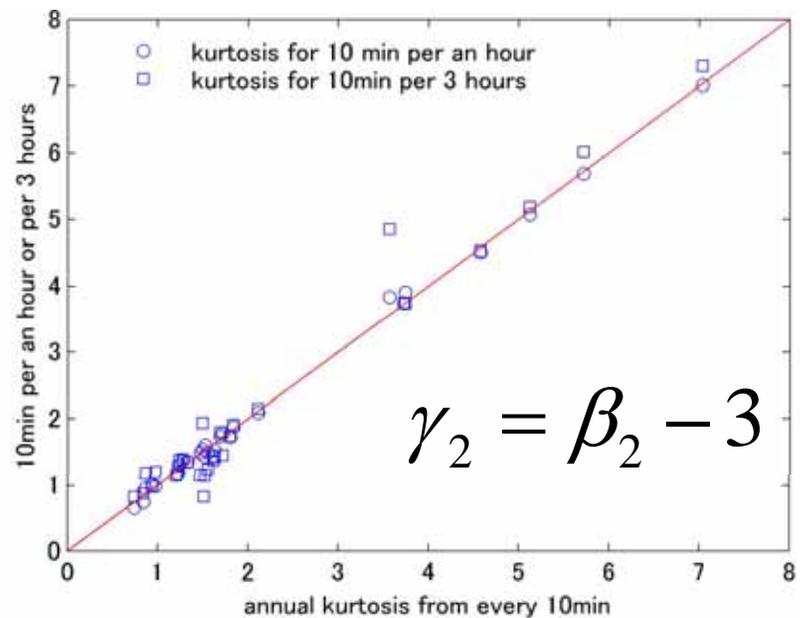
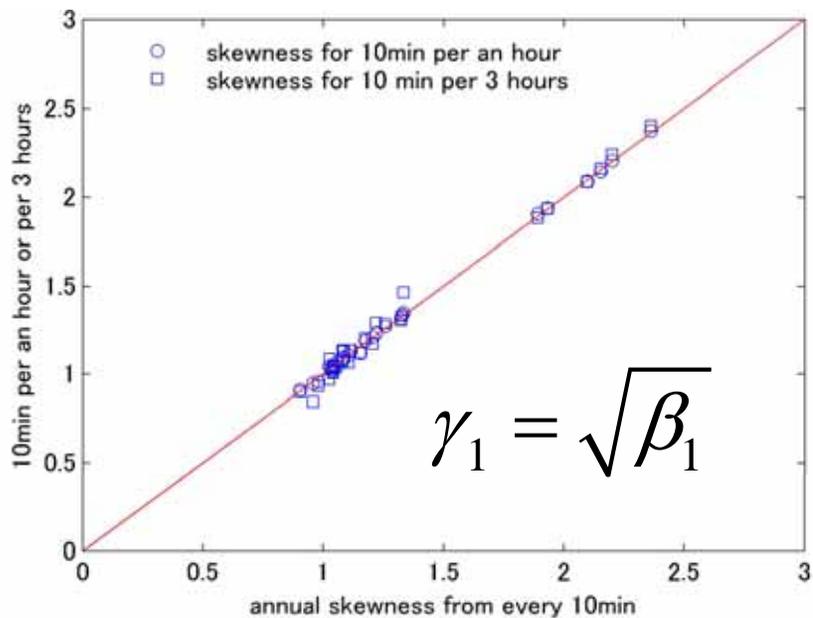
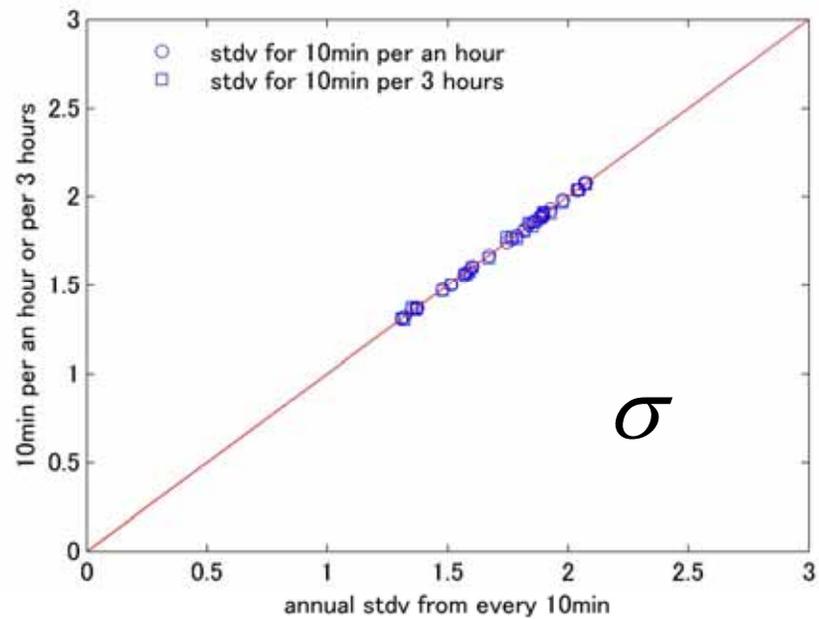
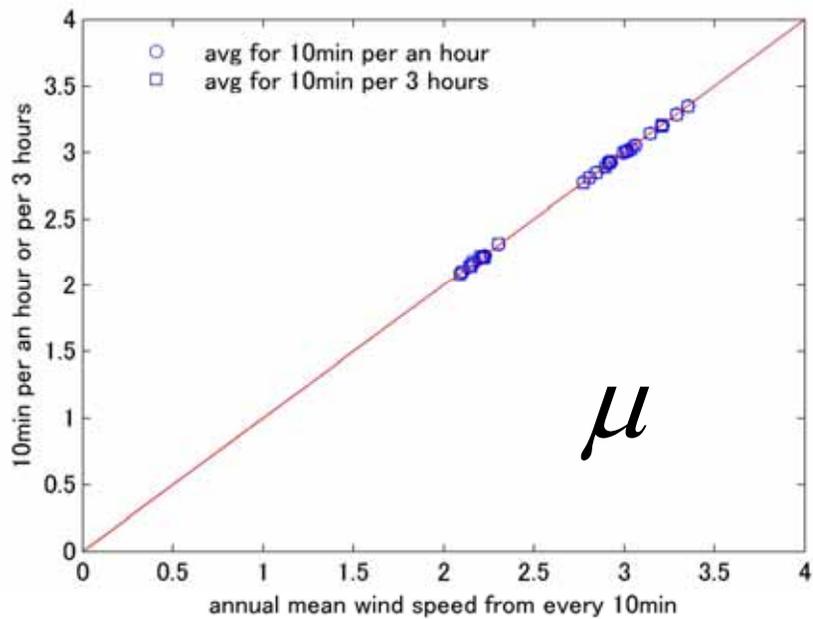
09 practical application:

Annual maximum wind speed in Japan



2) The effect of different observation recording format on the basic statistics

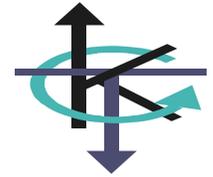
Base on the recently opened continuous 1 min average wind speed records (1997. 3~2002. 2), calculating every 10 min average wind speeds, 10 min average per hour and 3 hours, and comparing the basic statistics for each recording format, then the effect of different recording format becomes to be clear.



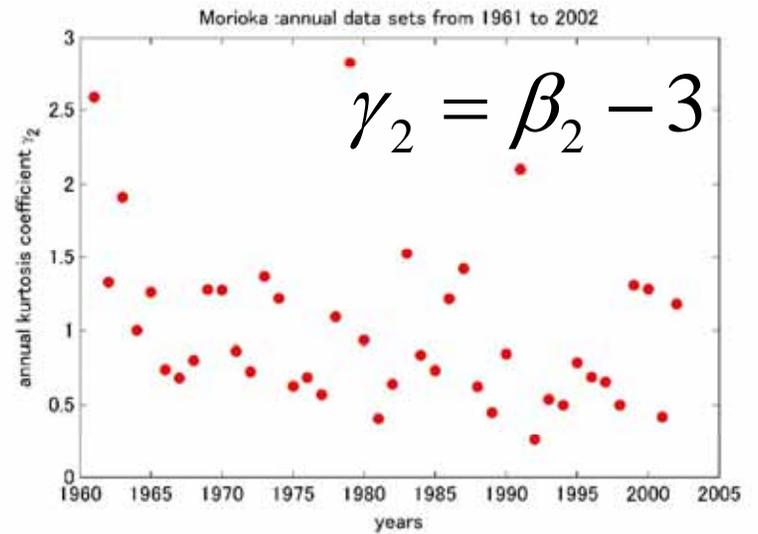
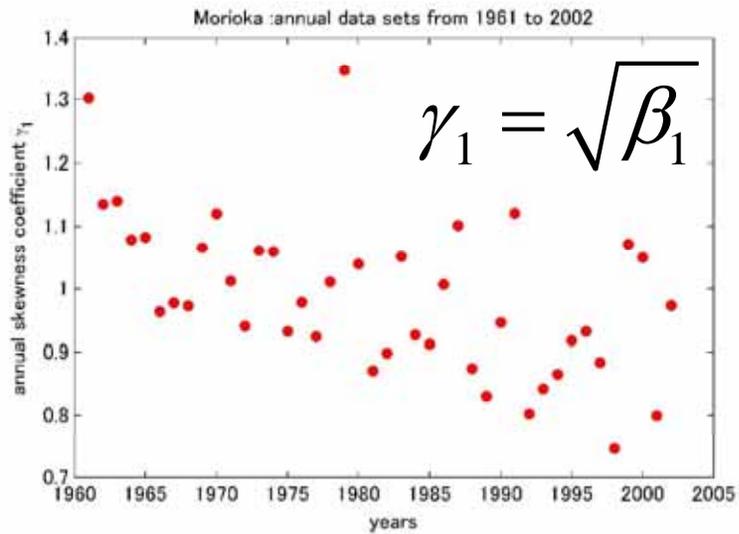
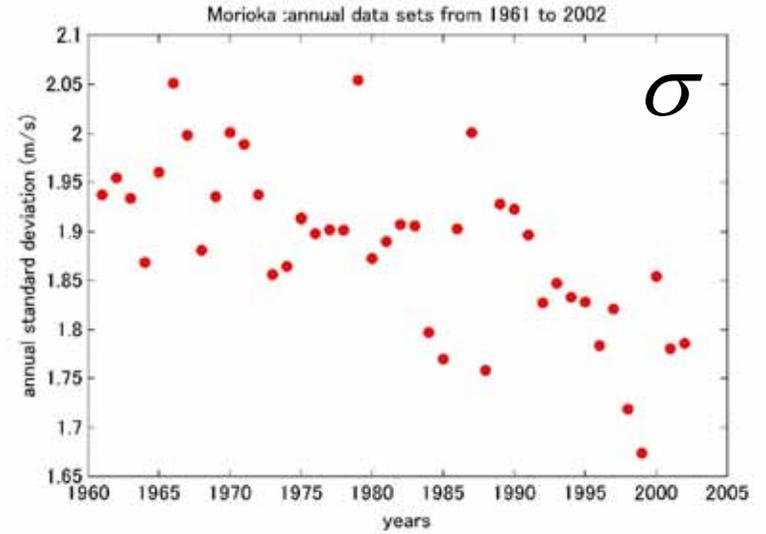
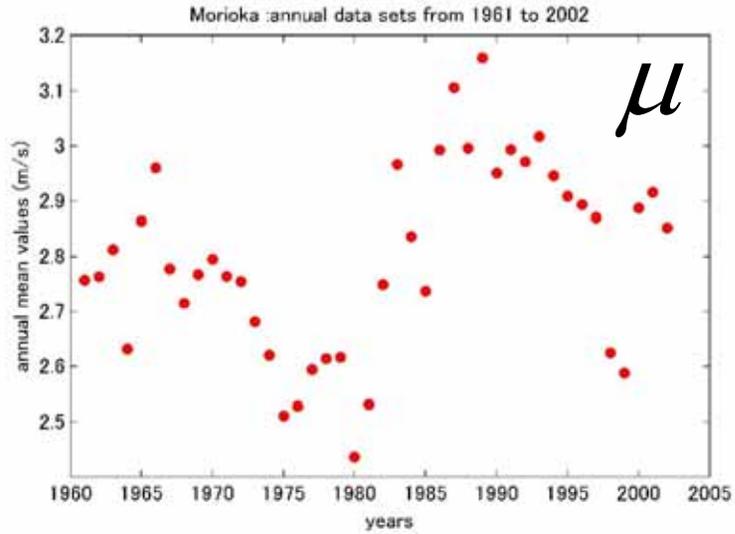
3) Examples of non-stationarity : the basic statistics (1961~2002)



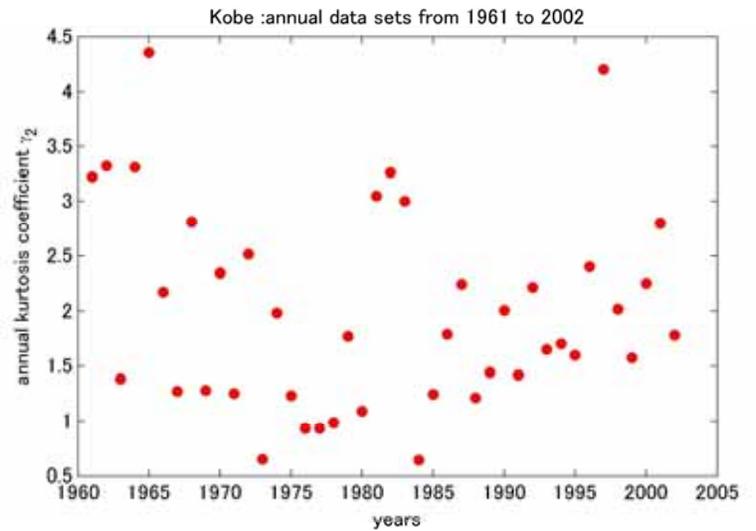
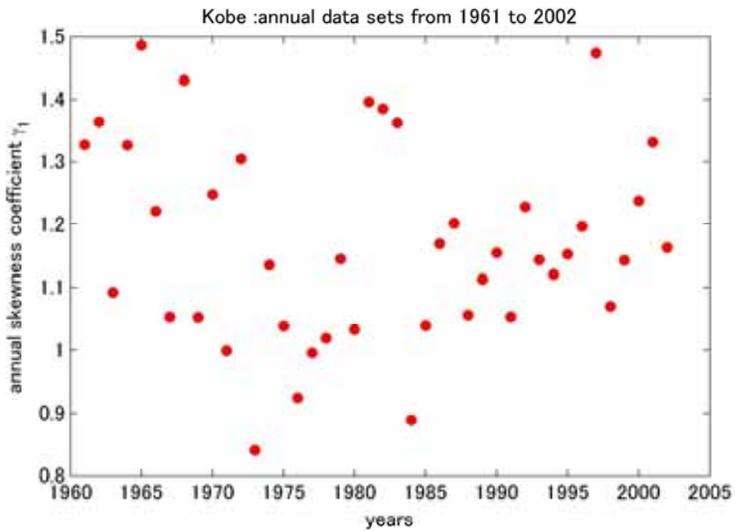
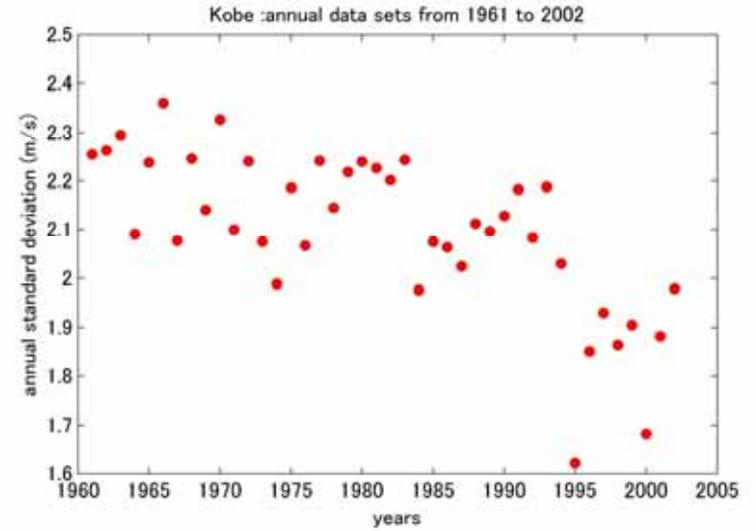
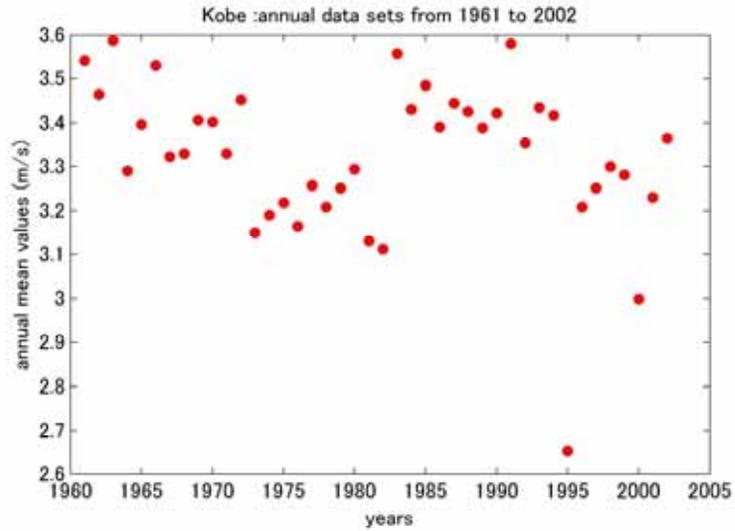
Site	Coefficient of Variations (C.O.V)			
	μ	σ	γ_1	γ_2
Abashiri	5.1%	5.0%	11.7%	14.4%
Katsuura	5.81%	8.87%	24.06%	26.71%
Kobe	5.71%	8.25%	12.55%	16.31%
Kumamoto	7.62%	5.93%	14.19%	32.36%
Makurazaki	4.60%	6.07%	25.97%	47.98%
Morioka	6.99%	4.43%	12.09%	11.55%
Oita	3.42%	8.41%	16.49%	27.41%
Shionomisaki	4.34%	4.07%	19.36%	30.10%
Tokyo	5.90%	8.06%	18.90%	17.88%
Minimum	3.42%	4.07%	11.72%	11.55%
Maximum	7.62%	8.87%	25.97%	47.98%



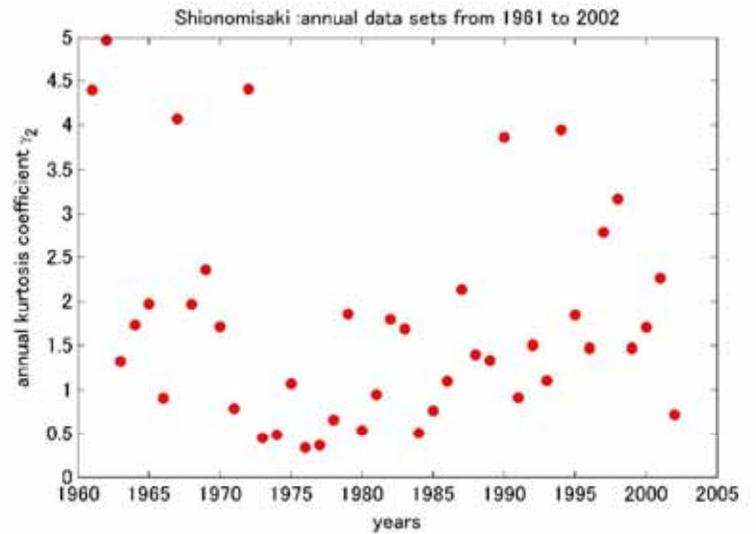
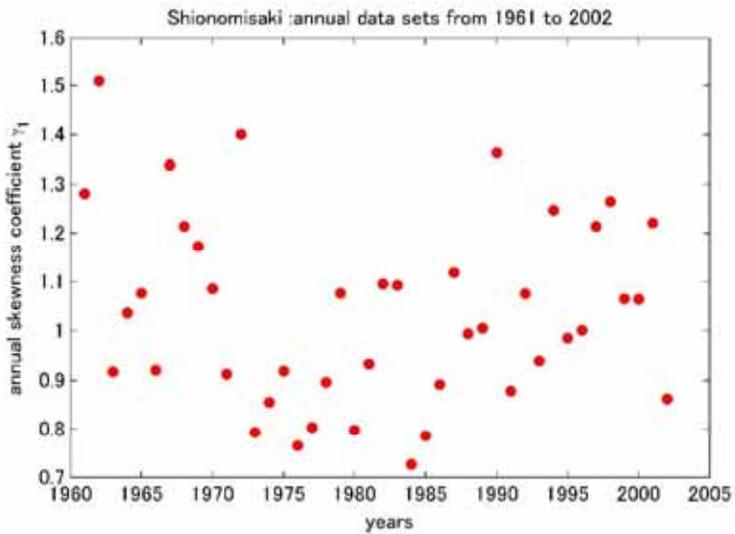
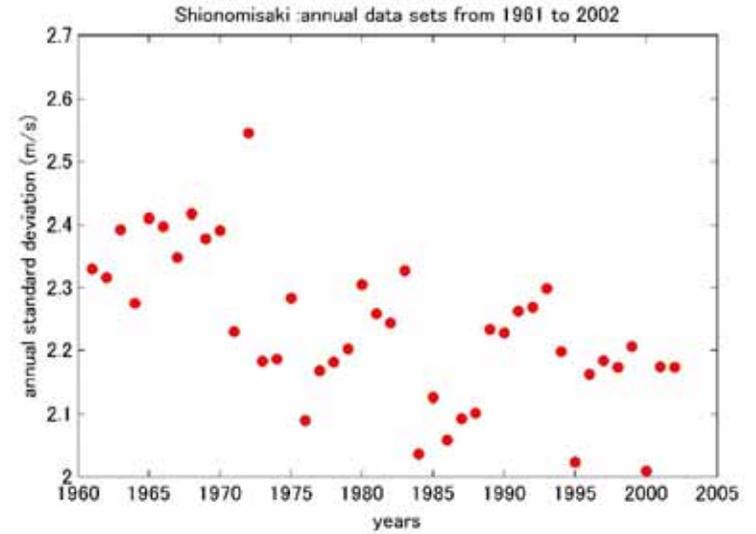
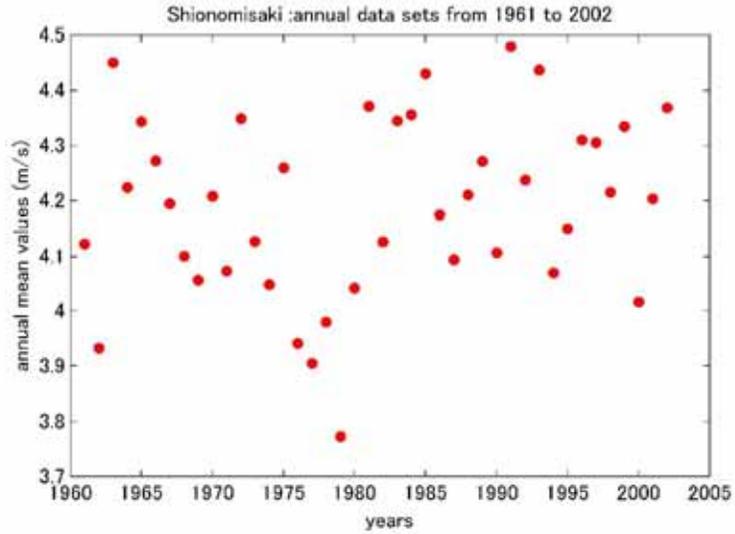
Morioka (1961~2002)



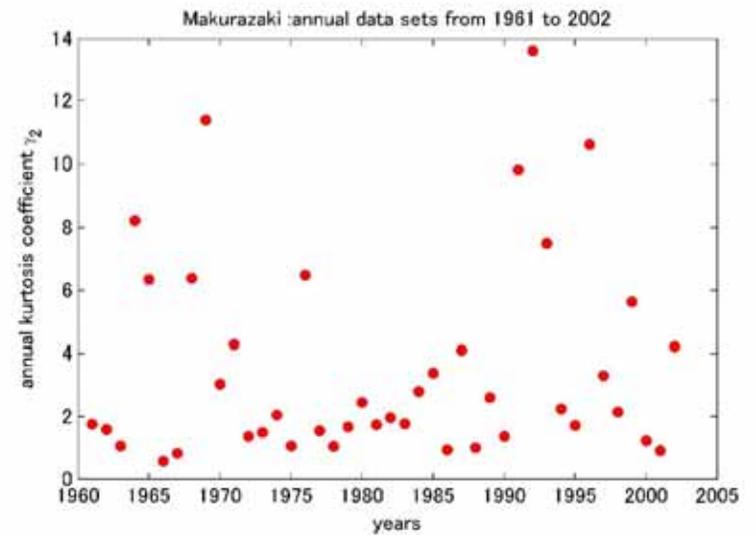
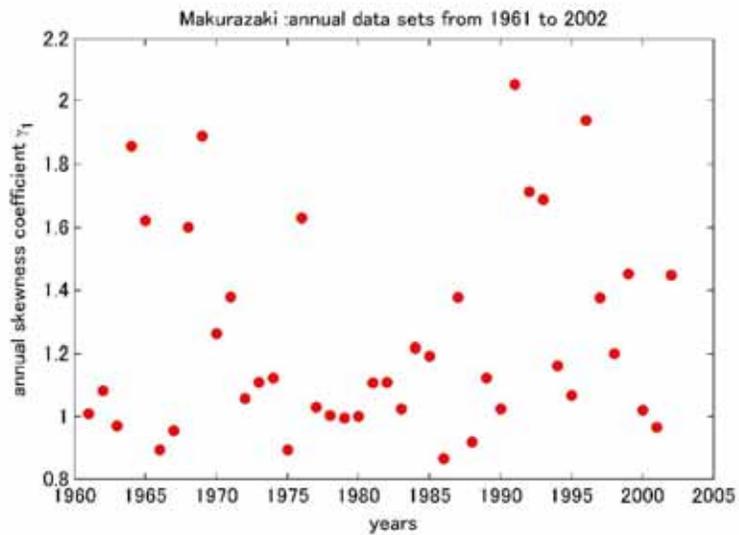
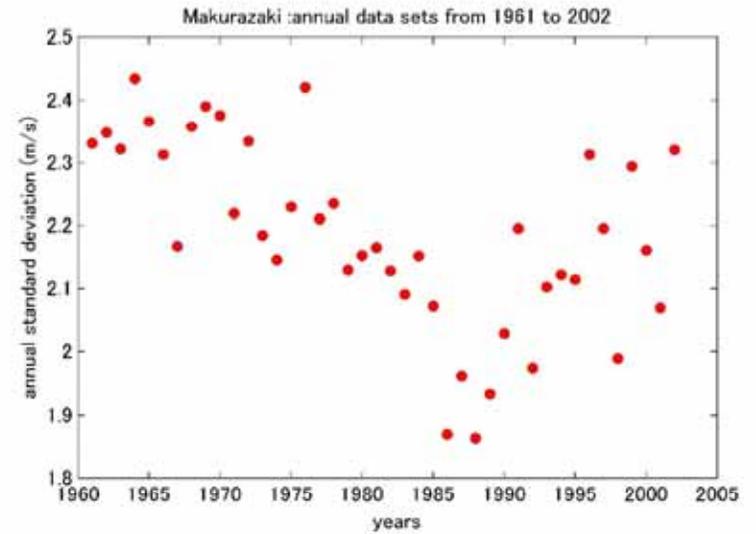
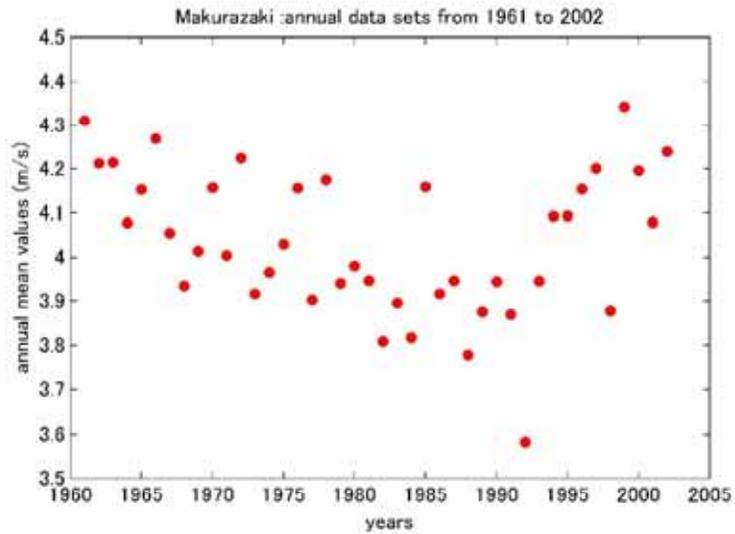
Kobe (1961~2002)



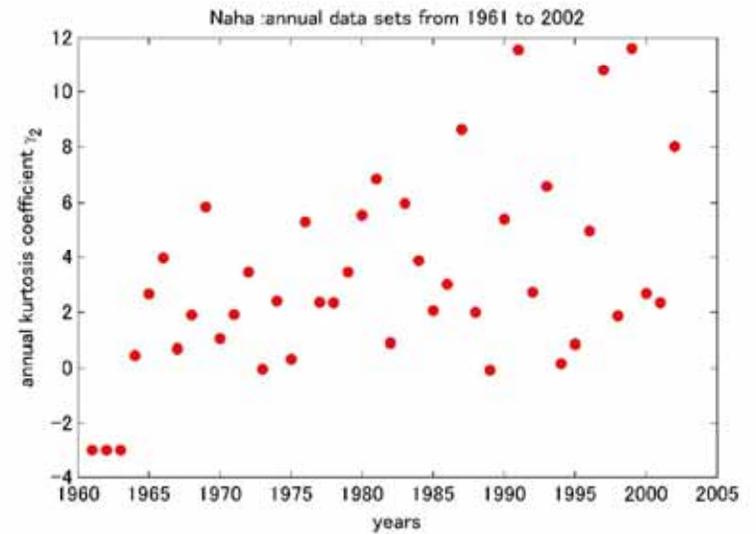
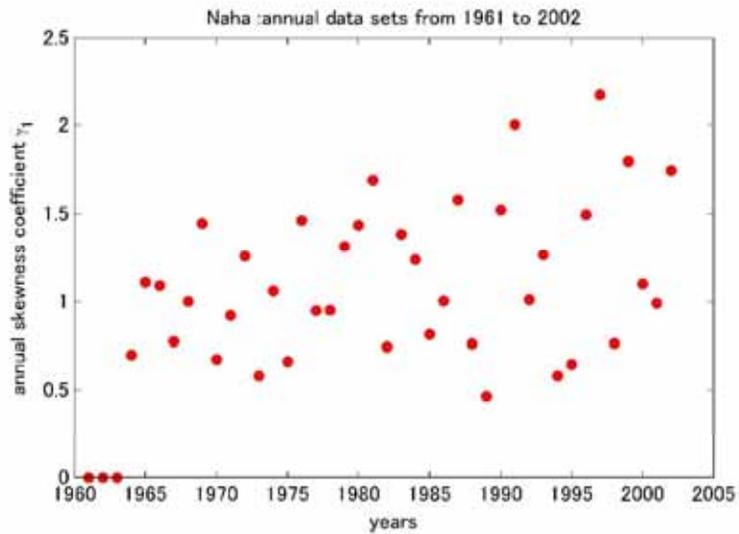
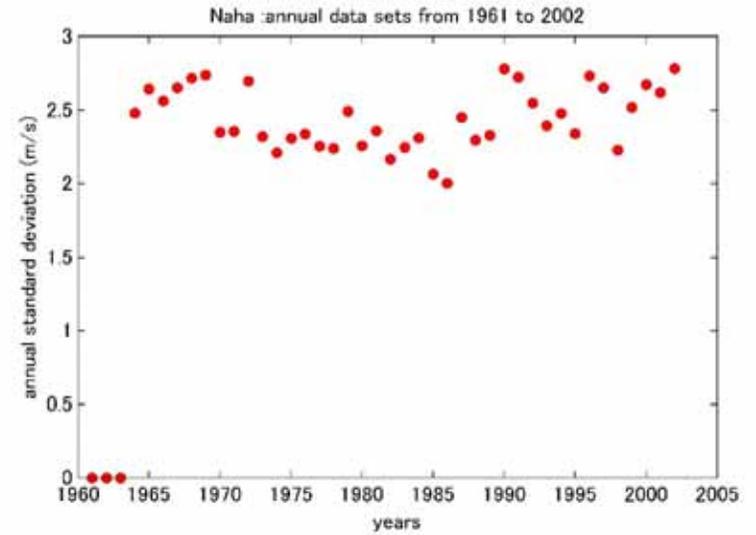
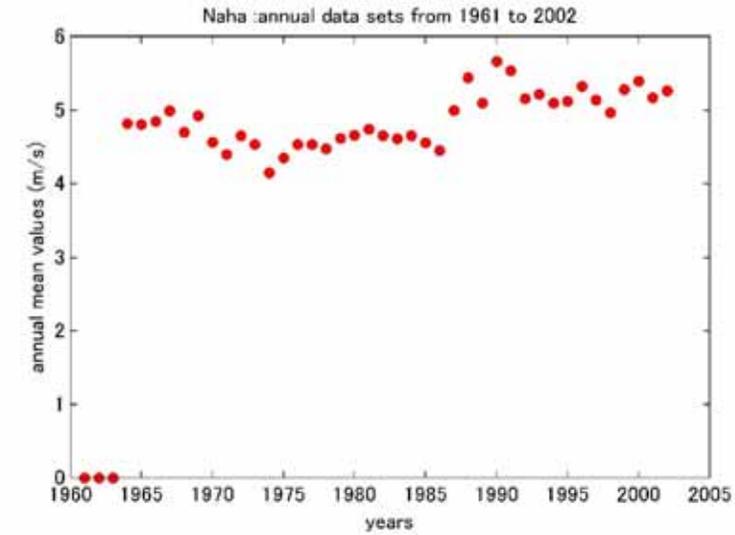
Shionomisaki (1961~2002)



Makurazaki (1961~2002)



Naha (1964~2002)



09 practical application:

Annual maximum wind speed in Japan



4) Approximation of the annual wind speed distribution

Based on the probability integral transformation,

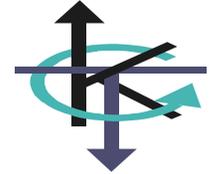
$$\Phi(z_\alpha) = F_{X_i}(x_\alpha) = F_{X_i}(g(z_\alpha)) = \alpha$$

$$x_\alpha = g(z_\alpha) = a + bz_\alpha + cz_\alpha^2 + dz_\alpha^3$$

$$\Rightarrow F_{X_i}(x_\alpha) = \Phi(g^{-1}(x_\alpha))$$

The coefficients a, b, c and d can be estimated from the given basic statistics of annual wind speed, i.e. mean, standard deviation, skewness and kurtosis (Choi & Kanda 2003).

5) Estimation by Monte Carlo Simulation (MCS)



5.1) Simulation methods

- ① **Based on the Spectral representation theorem for stationary stochastic process**
 - Using a given spectral density function, discrete stationary stochastic process is simulated.
 - time consuming method

- ② **Based on equivalent i.i.d. random sequence (EQRS)**
 - A stochastic process, which can be approximated by Poisson process, is modeled as an i.i.d. random sequence having same quantile function.
 - time effective method

5.2) Required information for MCS based on EQRS



- ① m : the number of Independent rv
→ approximated by mean zero crossing rate
(Normal process)

From **Rice theorem and Poisson approximation**, normal quantile function is given as follows:

$$z_\alpha = \sqrt{2 \{ \log \mu_0 T + y_T \}}$$

in which μ_0 : mean zero crossing rate, $y_T = -\log(-\log \alpha)$

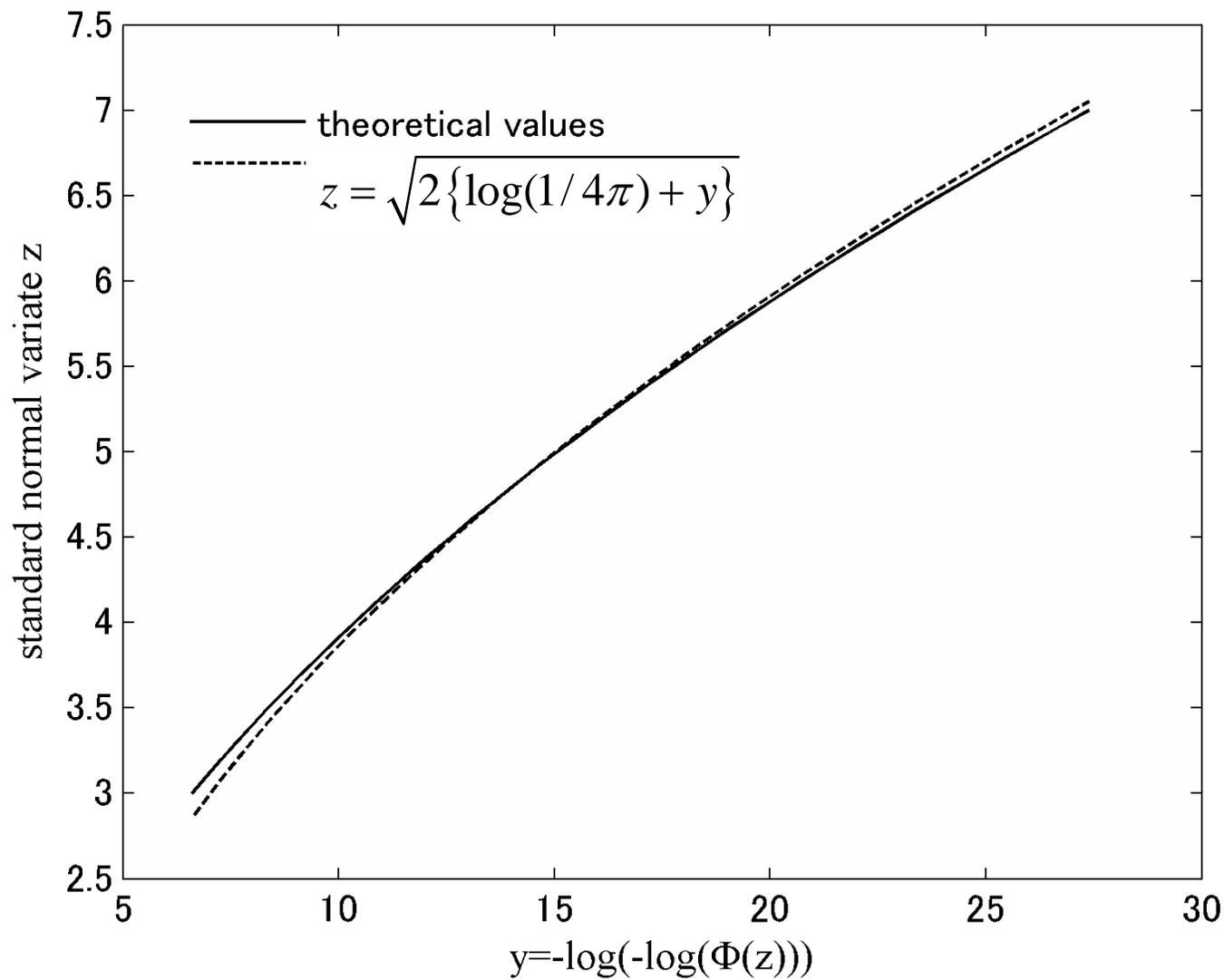
From $\Phi^m(z_\alpha)$,

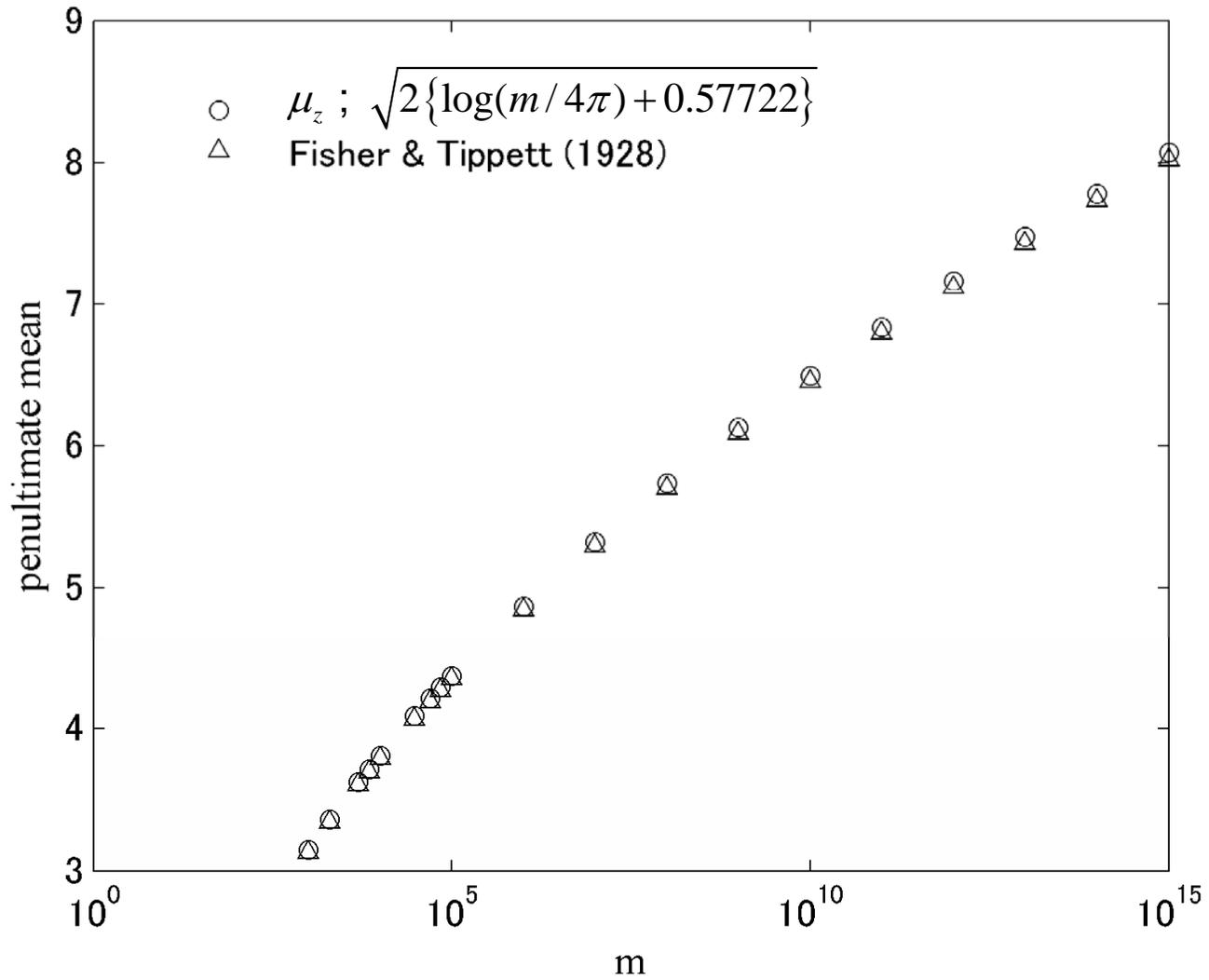
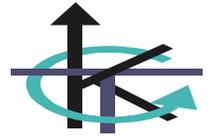
$$z_\alpha ; \sqrt{2 \{ \log (m / 4\pi) + y_T \}} *$$

By comparison,

$$m ; 4\pi\mu_0 T$$

* Choi & Kanda (2004), A new method of the extreme value distributions based on the translation method, *Summaries of Tech. Papers of Ann. Meet. of AIJ*, Vol. B1, p23~24 (in Japanese)





(non-Normal process)



To Rice formula for the expected number of crossings, i.e.

$$\nu(x) = \int_0^\infty \xi \cdot f(\xi | X = x) d\xi = f(x) \cdot \int_0^\infty \xi \cdot f(\xi) d\xi$$

applying translation function $g(z)$

$$\begin{aligned} \nu(x) &= \frac{1}{|g'(z)|} \phi(g^{-1}(x)) \cdot \int_0^\infty \frac{\xi \cdot \exp\left\{-\left(\xi / \sigma_\xi \cdot g'(z)\right)^2 / 2\right\}}{\sqrt{2\pi} \cdot \sigma_\xi \cdot g'(z)} d\xi \\ &= \frac{\sigma_\xi}{2\pi} \cdot \exp\left(-\frac{\{g^{-1}(x)\}^2}{2}\right) = \nu_0 \cdot \exp\left(-\frac{\{g^{-1}(x)\}^2}{2}\right) * \end{aligned}$$

From Poisson approximation

$$x_\alpha = g(z_\alpha) = g\left(\sqrt{2\{\log(\nu_0 T) + y_T\}}\right)$$

With the same manner

$$m ; 4\pi\nu_0 T$$

* The distribution of dx/dt is assumed as normal distribution and the assumption is reasonable. e.g. H. Choi (1988), *Characteristics of natural wind for wind load estimation*, Master Thesis, Univ. of Tokyo (in Japanese)

Practical example ($T=1$ year)

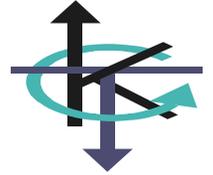


- $\nu_0 T$ estimated from long term observation records in Tokyo (1985~1987, Choi 1988)

Height (m)	45	45	46	48	58
$\nu_0 T$	2883	2665	2545	2739	2307
Height (m)	63	79	93	187	
$\nu_0 T$	3124	2586	3115	2384	

$$m = 4\pi\nu_0 T = 4\pi \cdot (2300 \sim 3000) \rightarrow 30,000$$

5.2) Required information for MCS based on EQRS



② parent distribution function for each year

→ Generalized bootstrap method +

Translation method (Probability Integral Transform)

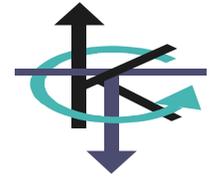
For the year i ,

$$F_i(x = g_i(z)) = \Phi(z), \quad g_i(z) = a_i + b_i z + c_i z^2 + d_i z^3$$

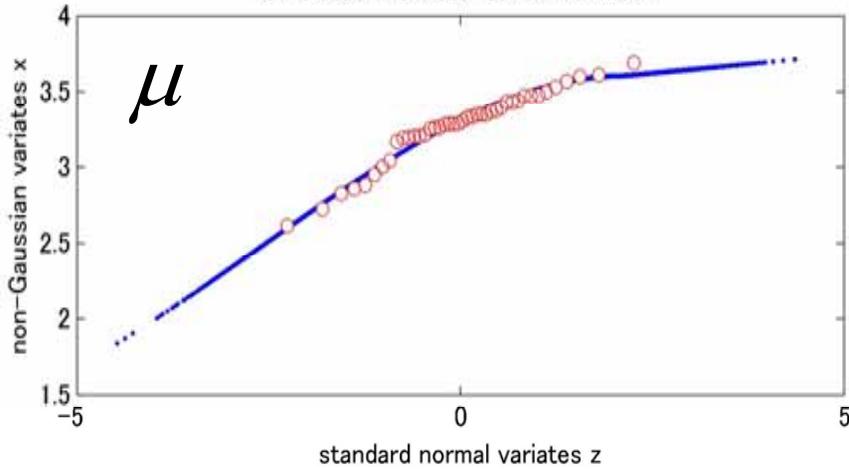
$$\{a, b, c, d\}_i = \Psi(\mu_i, \sigma_i, \gamma_{1i}, \gamma_{2i})$$

$$\max(x_1, \mathbf{K}, x_m)_{i=1, \mathbf{K}, n} = g_i(\max(z_1, \mathbf{K}, z_m)_{i=1, \mathbf{K}, n})$$

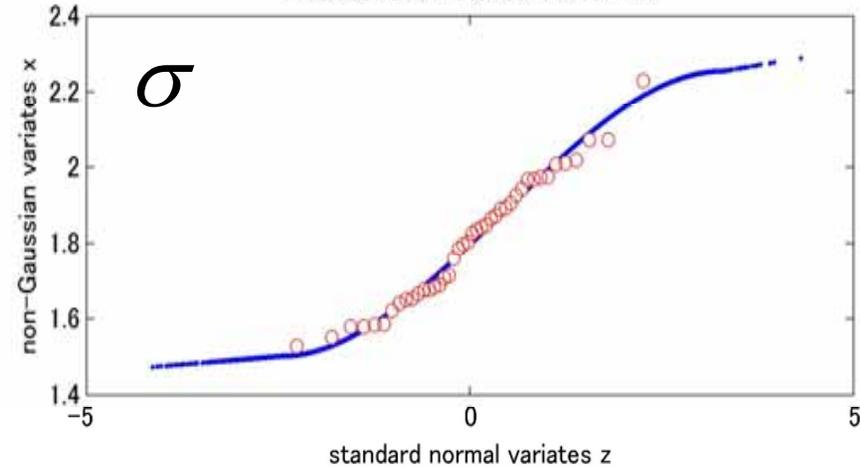
Example : Tokyo (1961~2002)



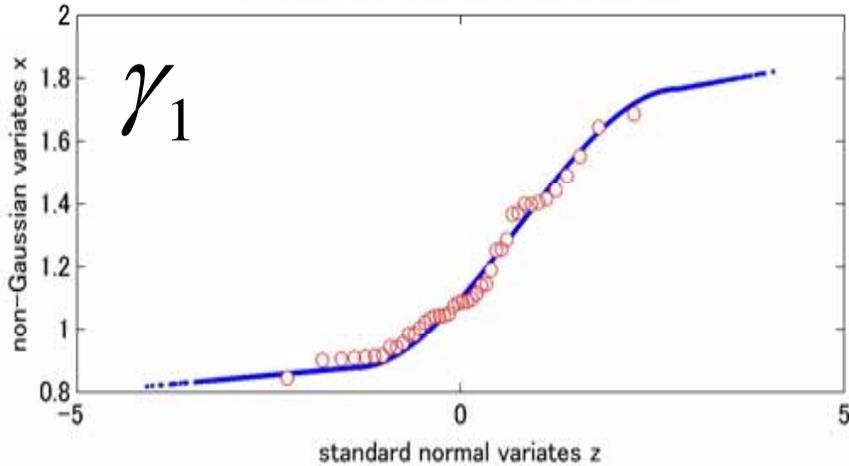
simulated and historical annual mean



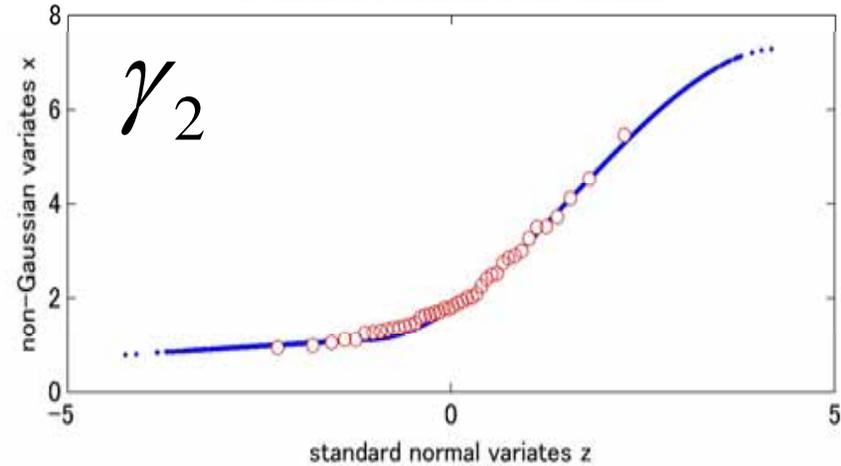
simulated and historical annual rms



simulated and historical annual skewness



simulated and historical annual kurtosis



○ Estimated from historical records ■ Monte Carlo Simulation



Correlation between the basic statistics (Tokyo)

	μ	σ	γ_1	γ_2
μ	1.000	0.242	-0.372	-0.315
σ	0.242	1.000	0.541	0.433
γ_1	-0.372	0.541	1.000	0.946
γ_2	-0.315	0.433	0.946	1.000

Such correlation characteristics between the basic statistics are regenerated by Cholesky decomposition of correlation matrix.

Regeneration of correlation characteristics

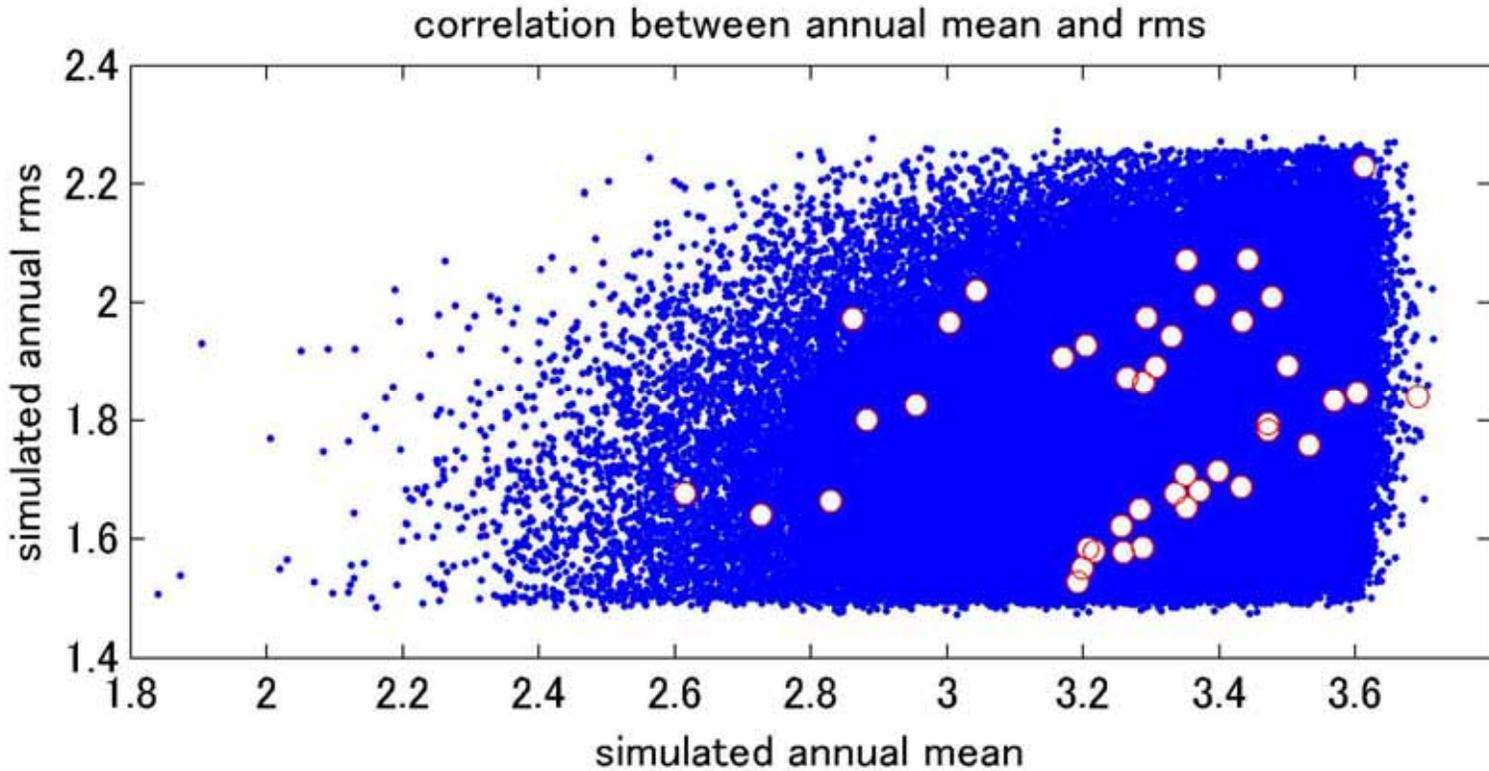


correlation coefficients of simulated ones and given values

	μ	σ	γ_1	γ_2
μ	1.000	0.242 (0.242)	-0.389 (-0.372)	-0.343 (-0.315)
σ	0.242 (0.242)	1.000	0.565 (0.541)	0.476 (0.433)
γ_1	-0.389 (-0.372)	0.565 (0.541)	1.000	0.958 (0.946)
γ_2	-0.343 (-0.315)	0.476 (0.433)	0.958 (0.946)	1.000

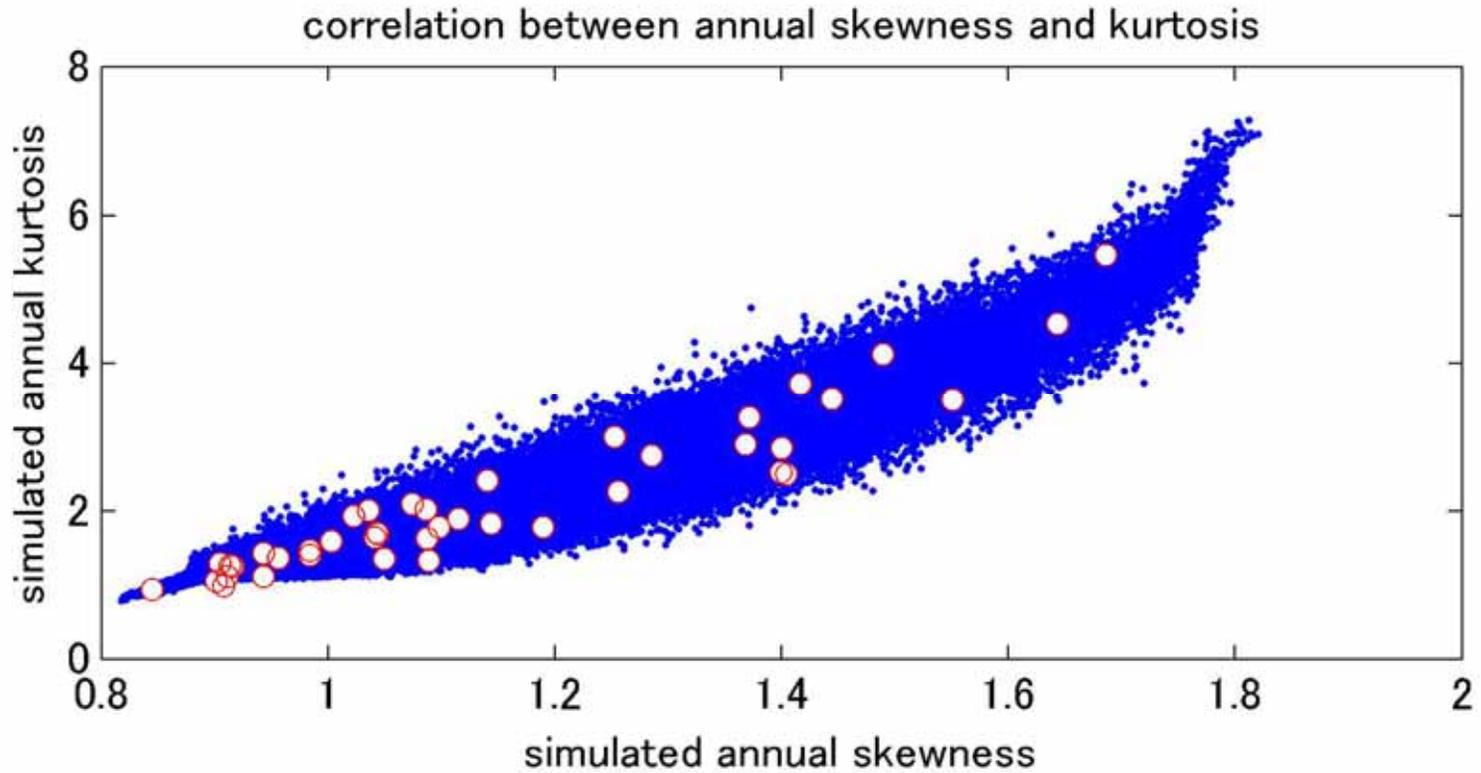
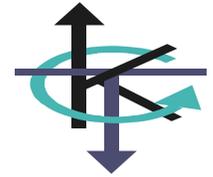
(•): given correlation coefficient

No. of Simulation : n=100 year x 1000 times



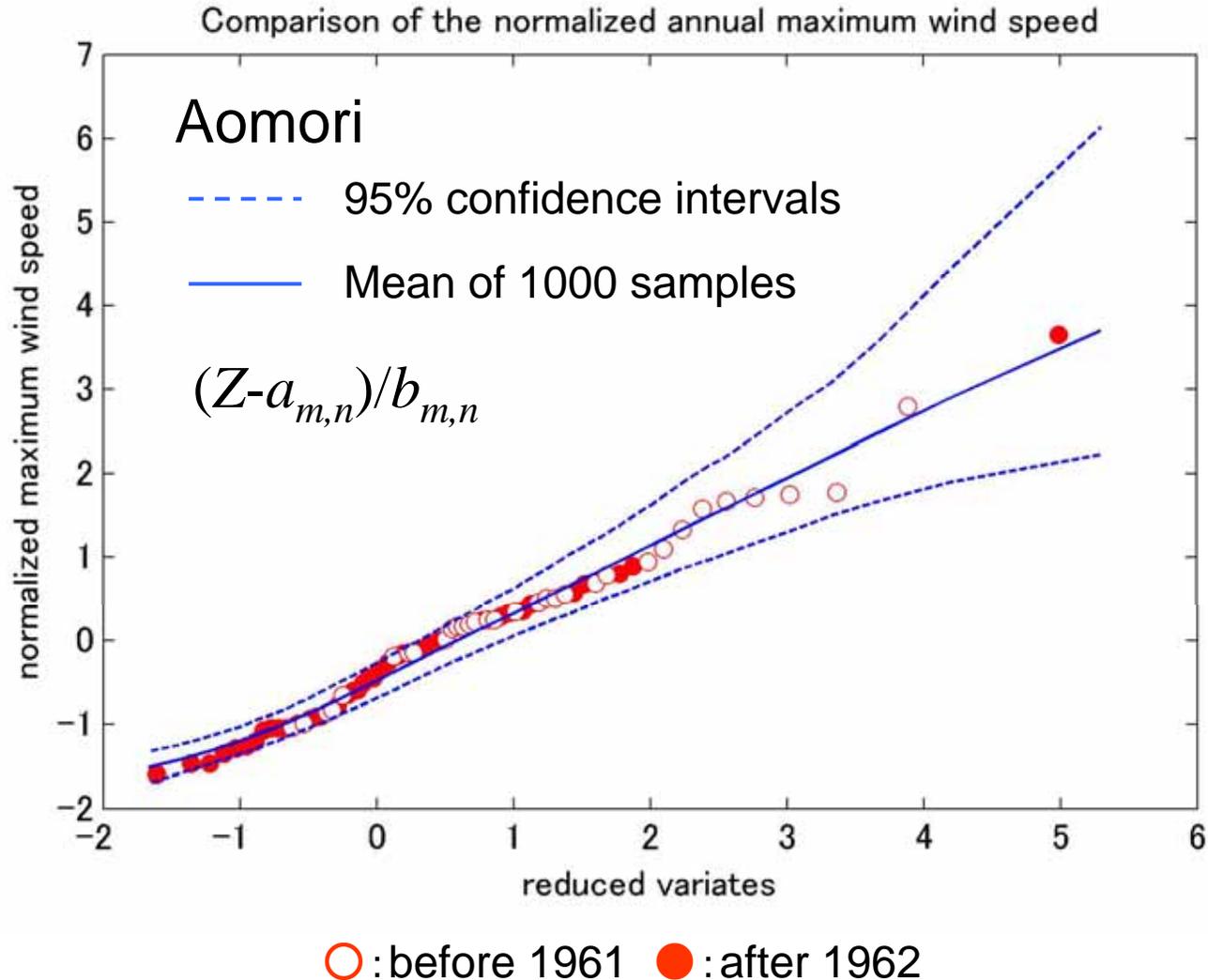
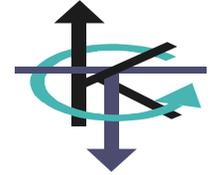
○ : annual mean and standard dev. from historical records

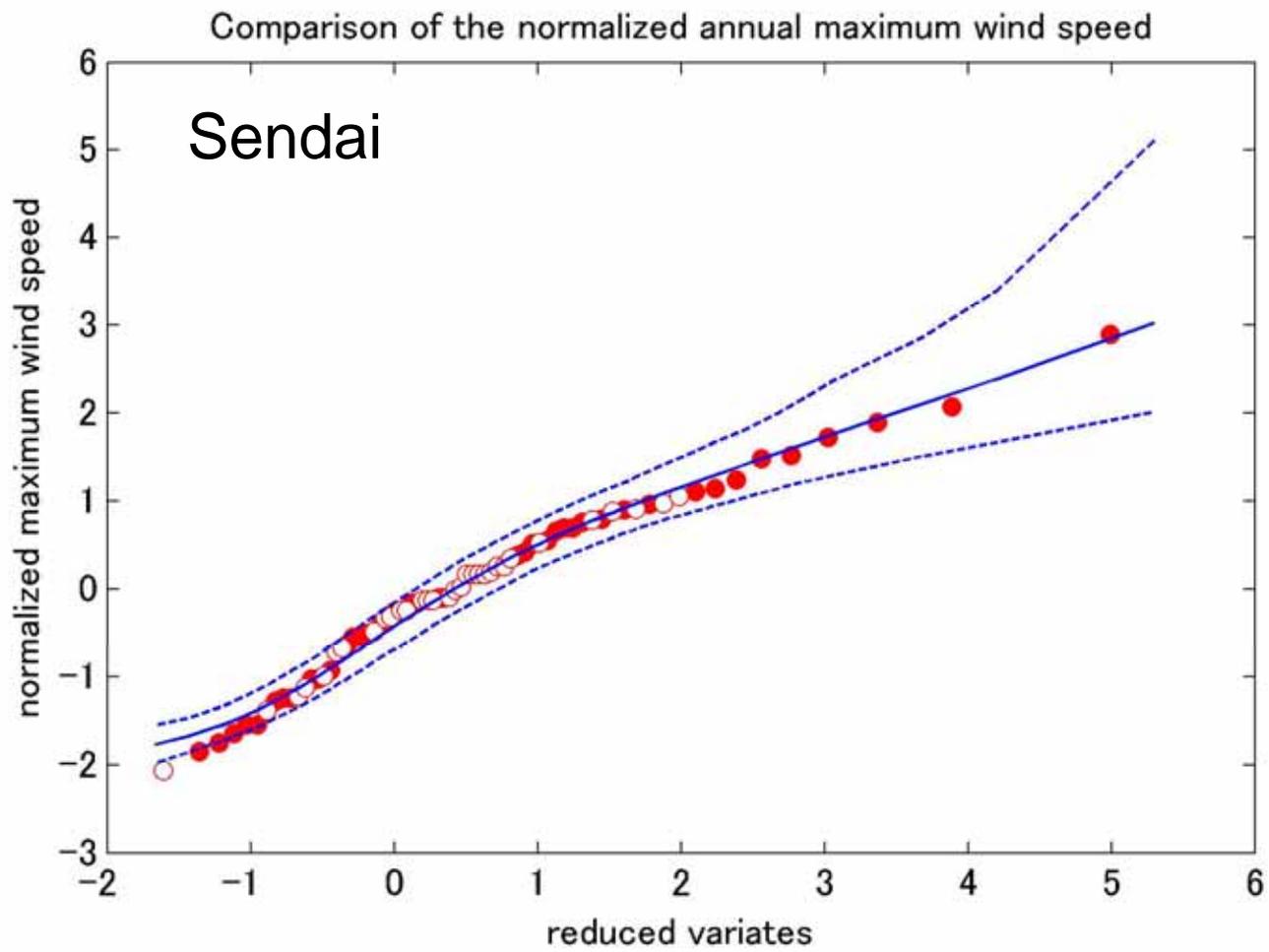
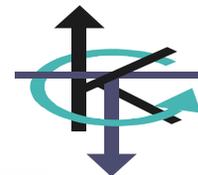
No. of Simulation : n=100 years x 1000 times

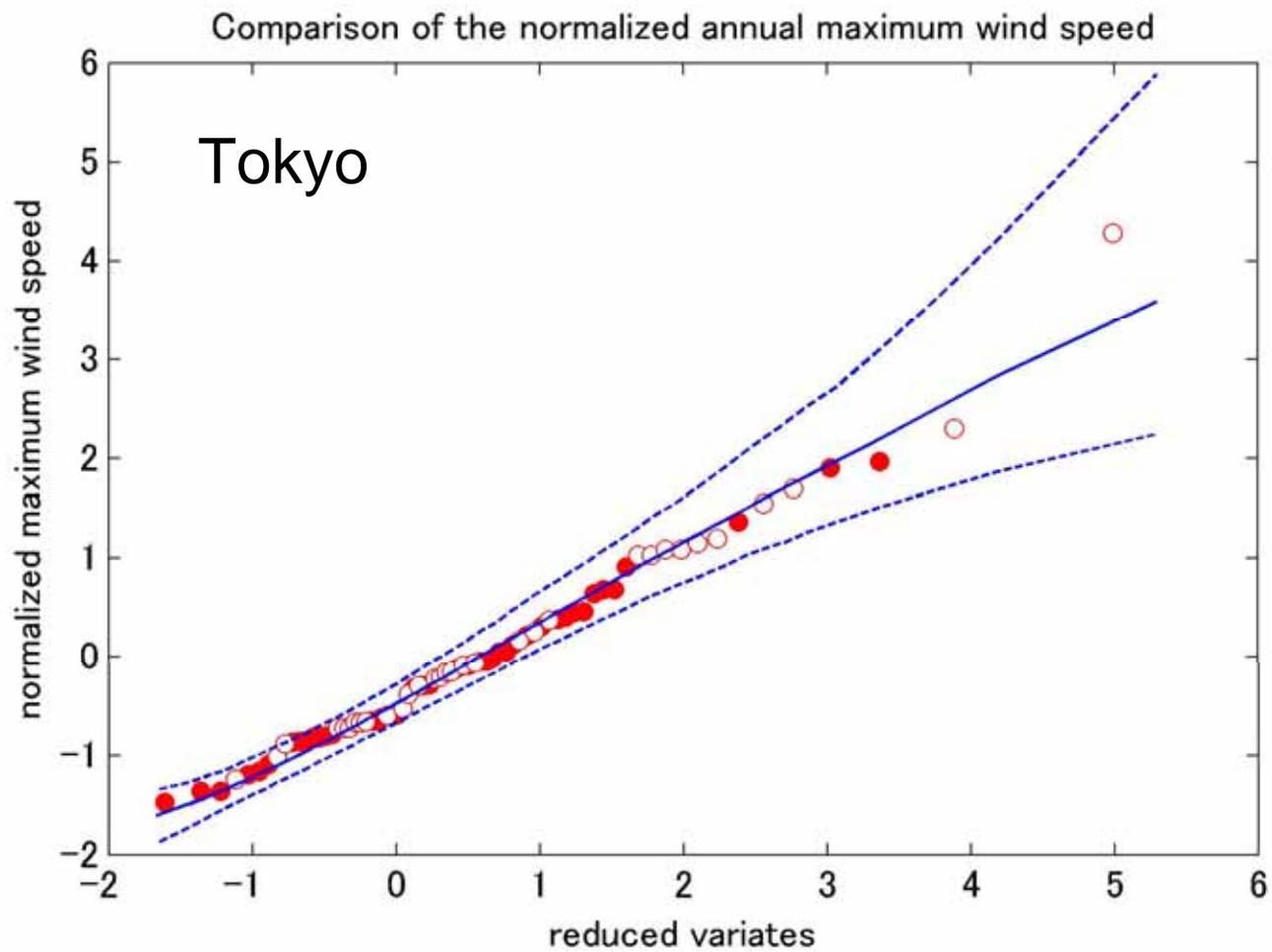
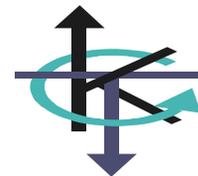


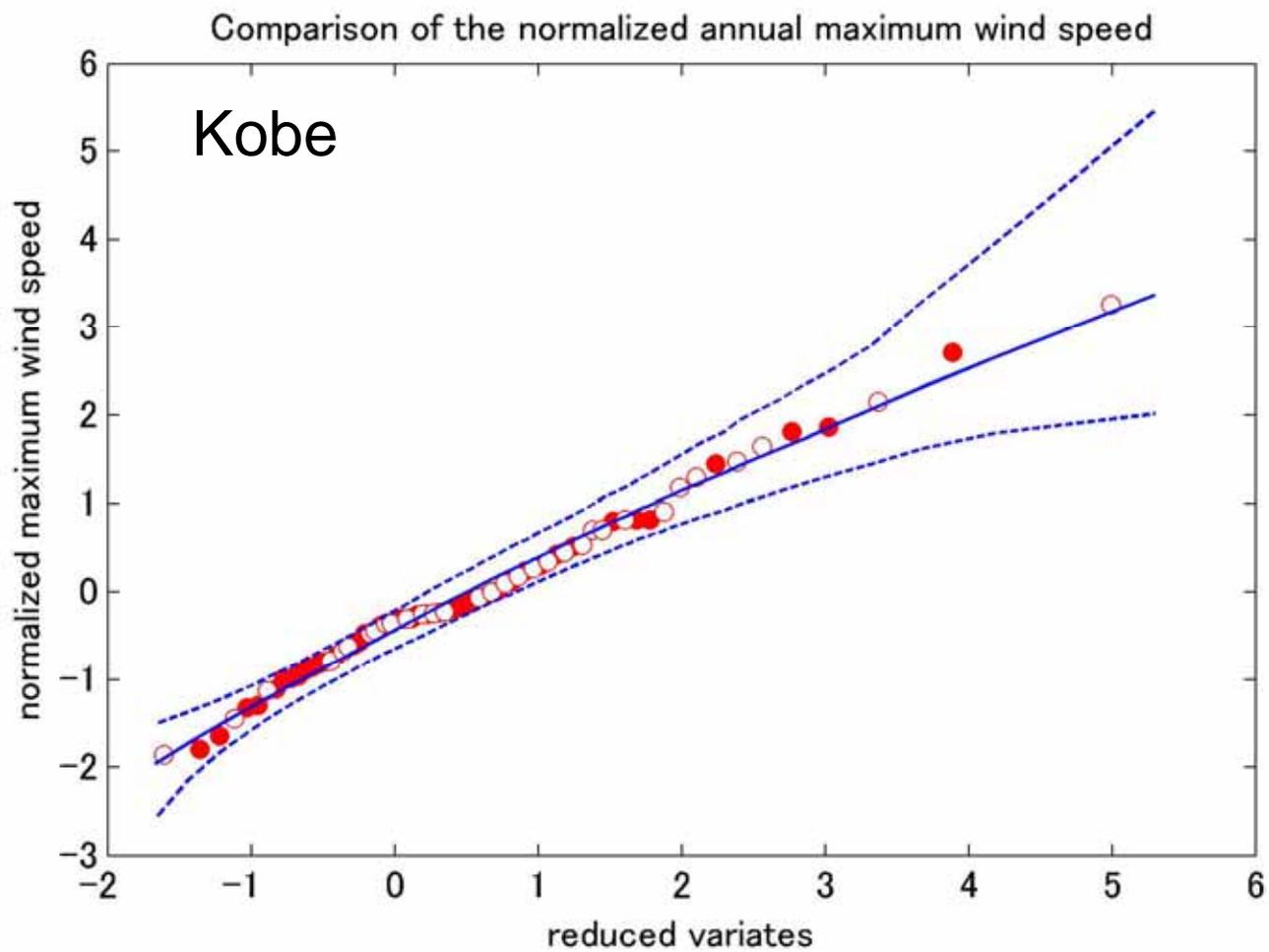
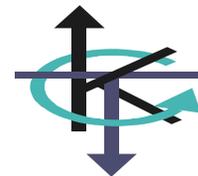
○ : skewness and kurtosis from historical records

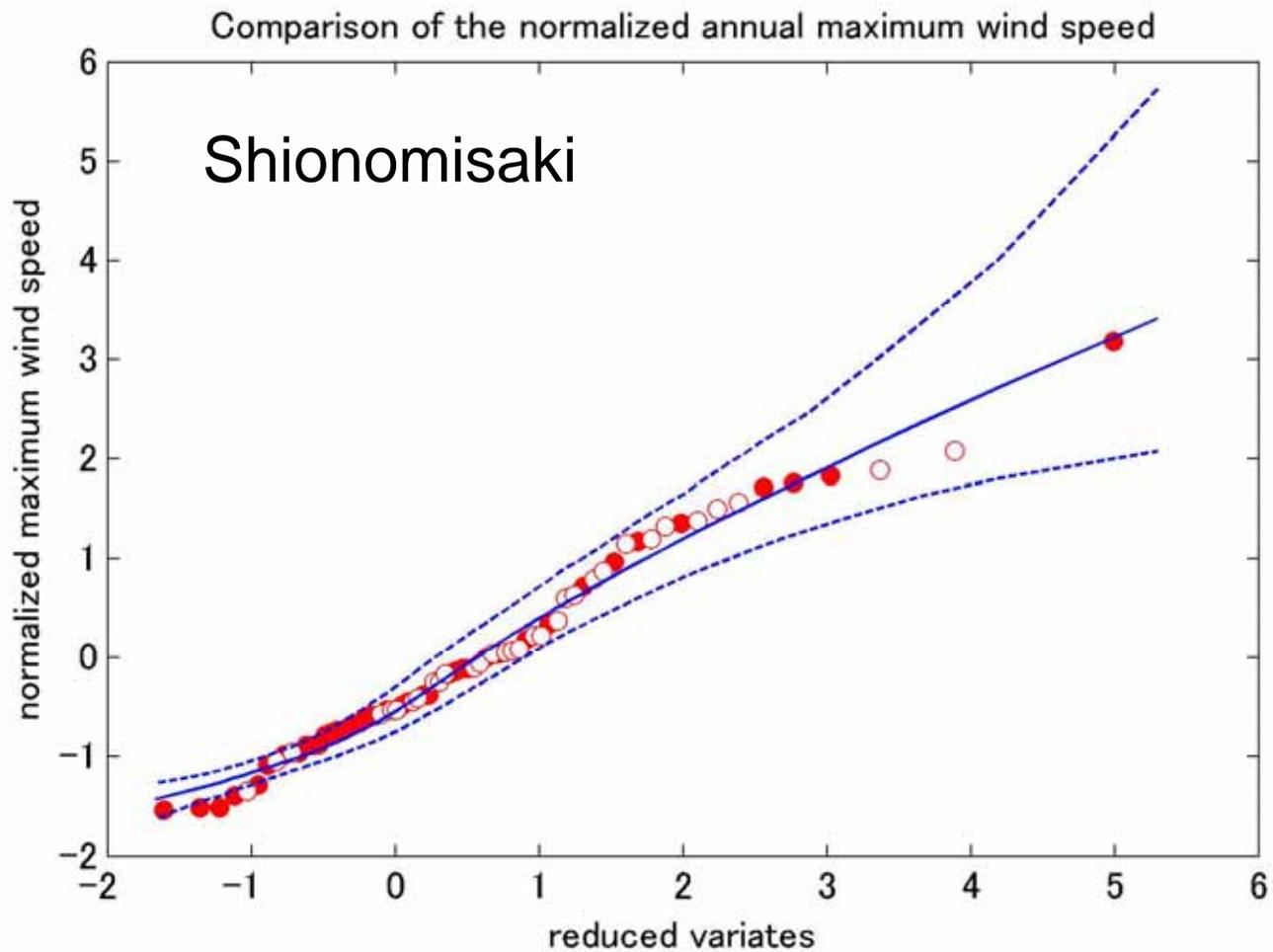
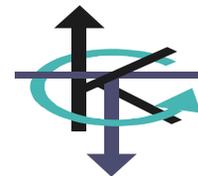
6) Comparison of the quantile functions from MCS and historical records in normalized form

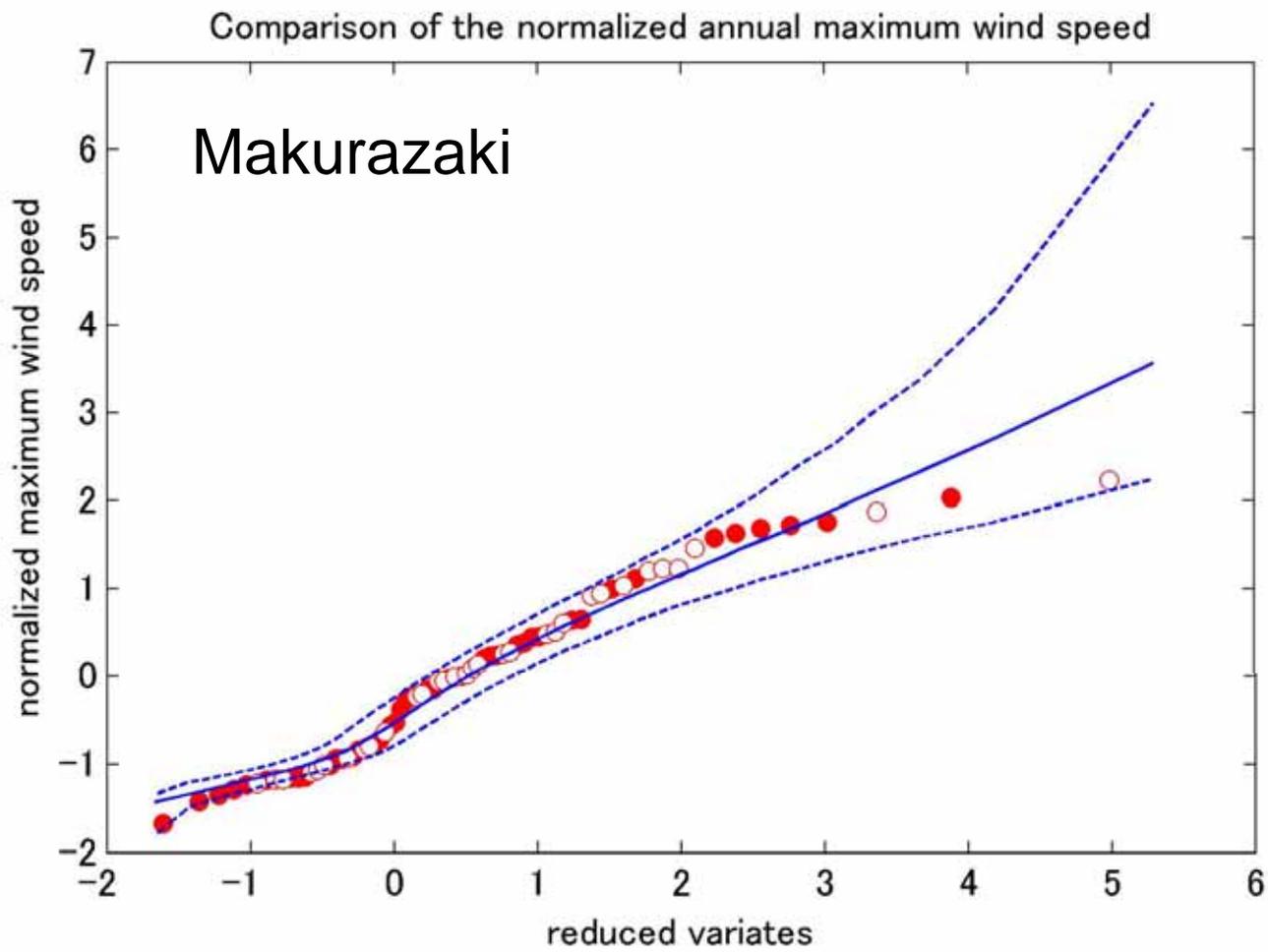
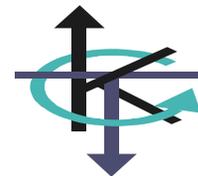


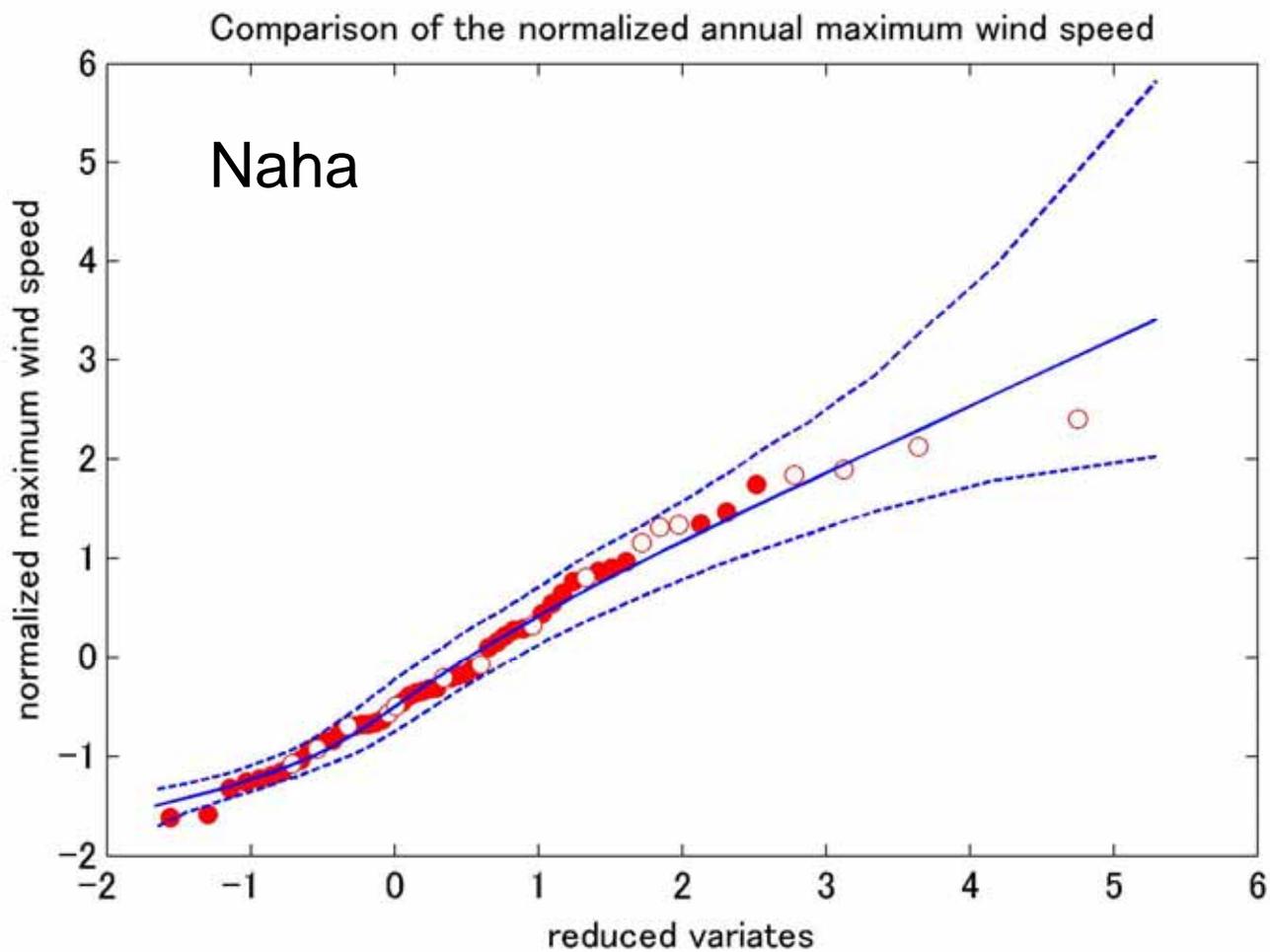
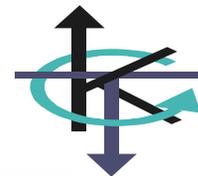




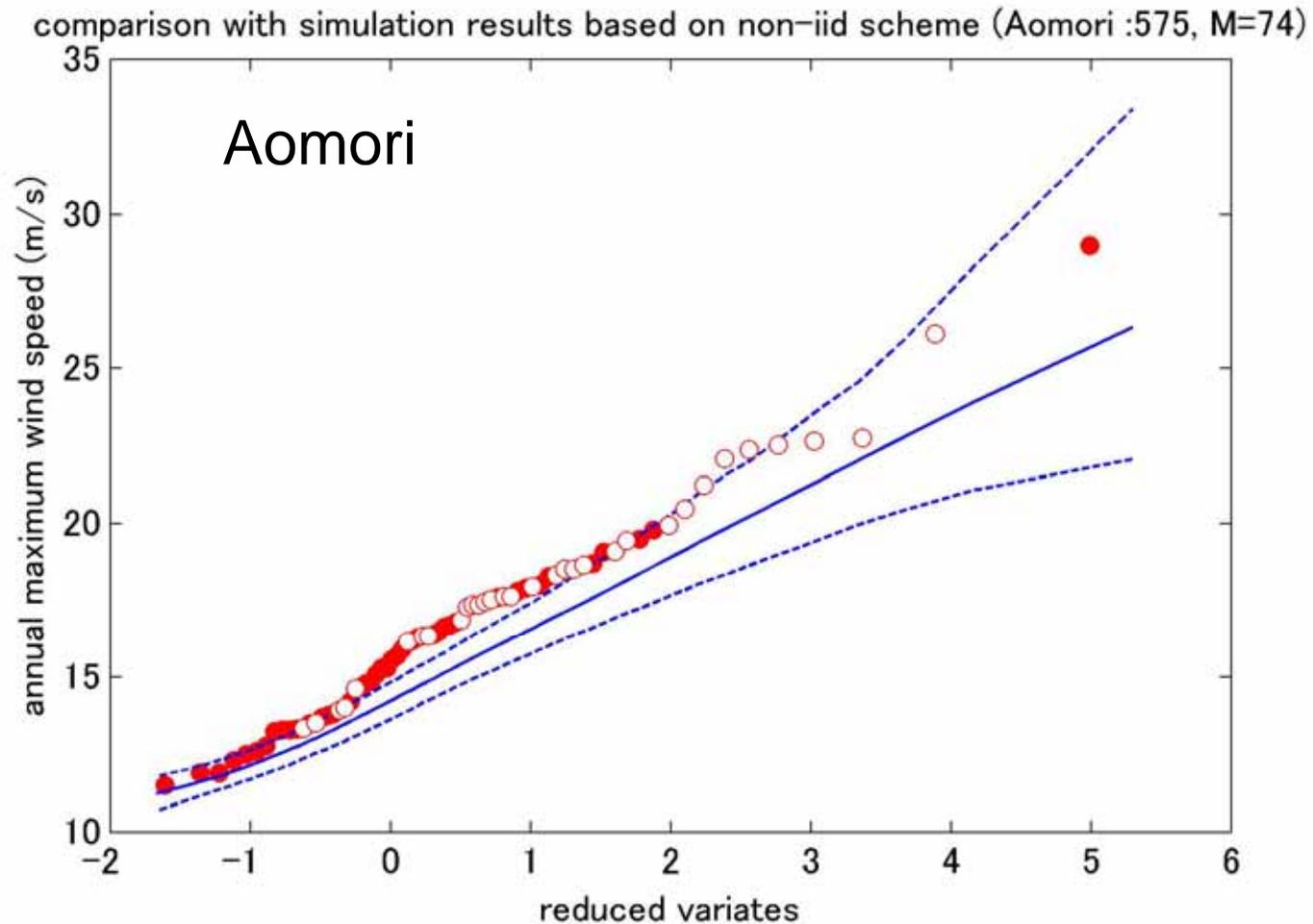


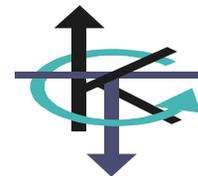




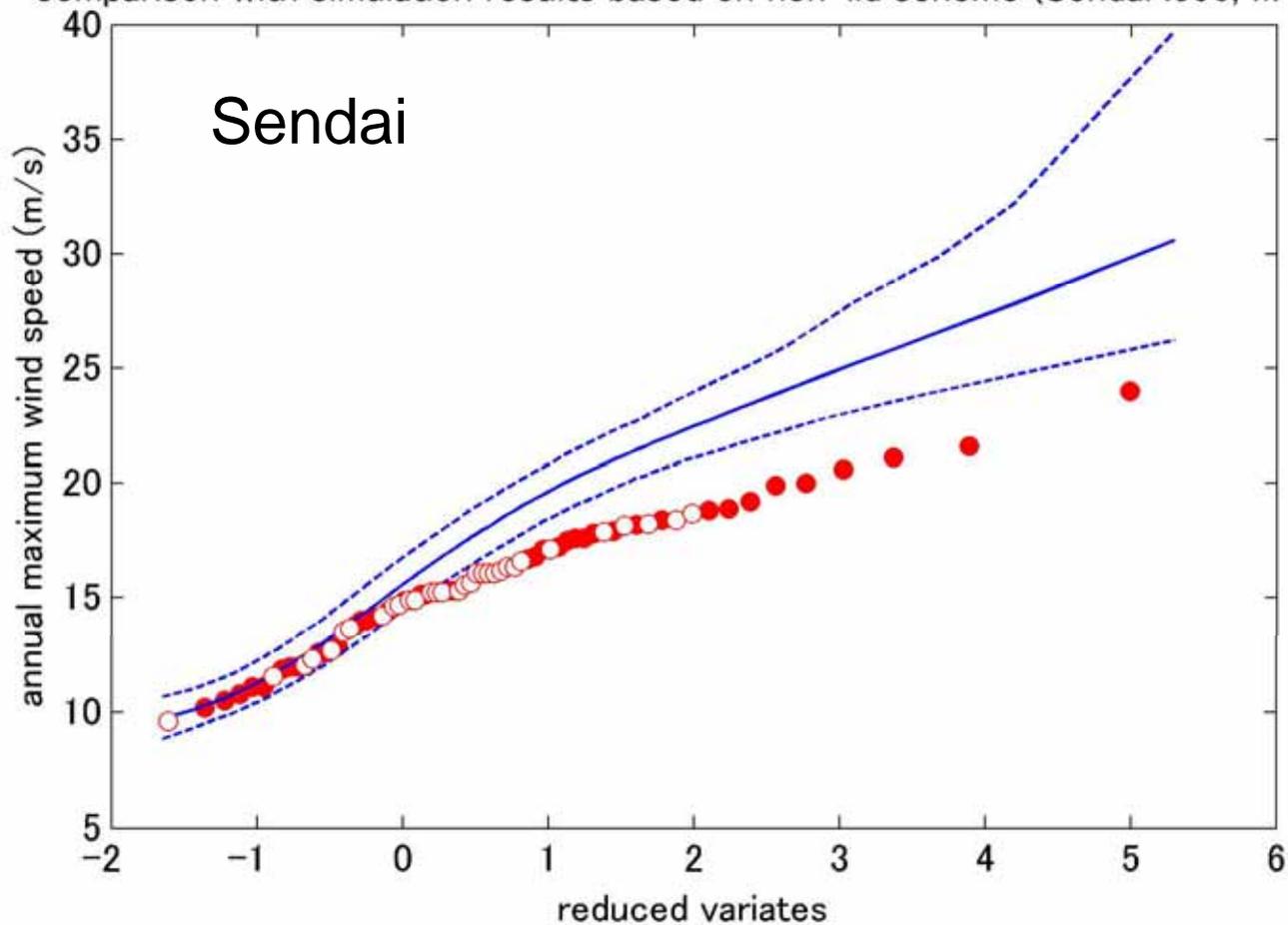


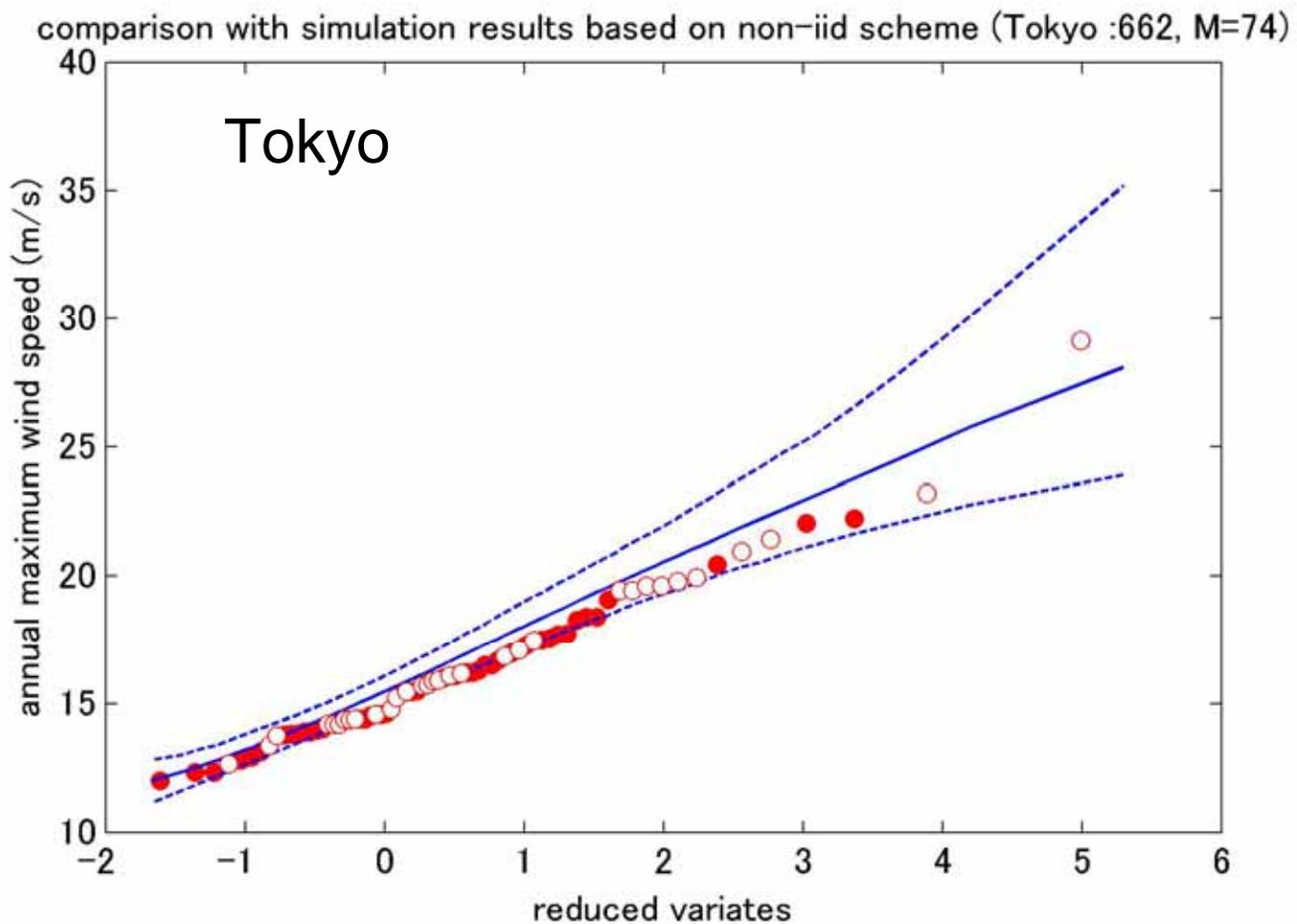
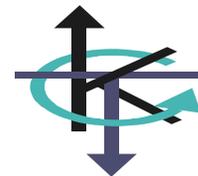
7) Comparison of the quantile functions from MCS and historical records in full scale

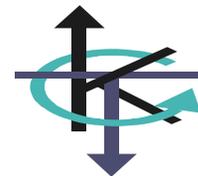




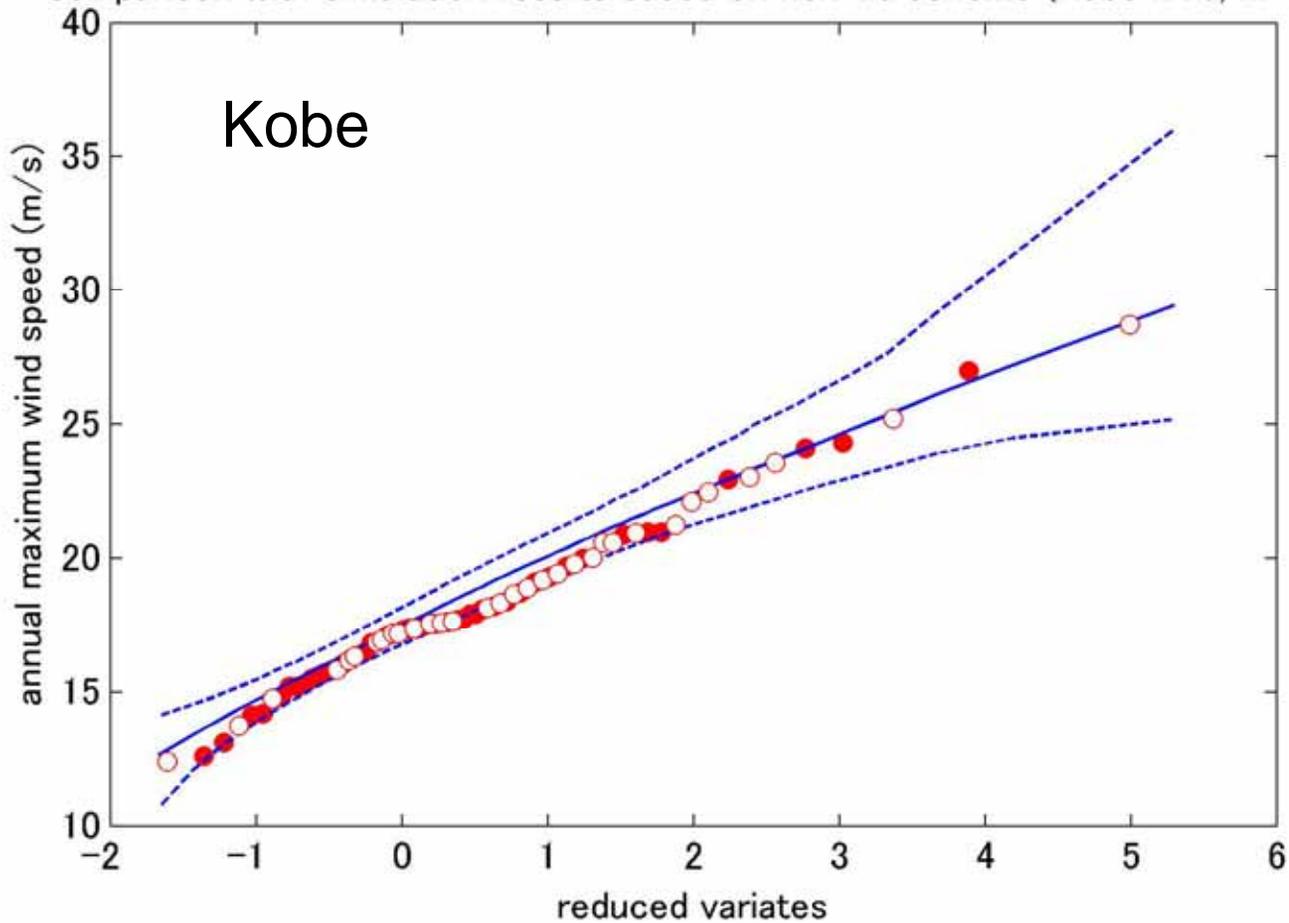
comparison with simulation results based on non-iid scheme (Sendai :590, M=74)

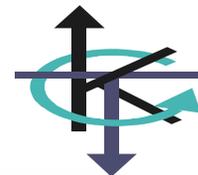




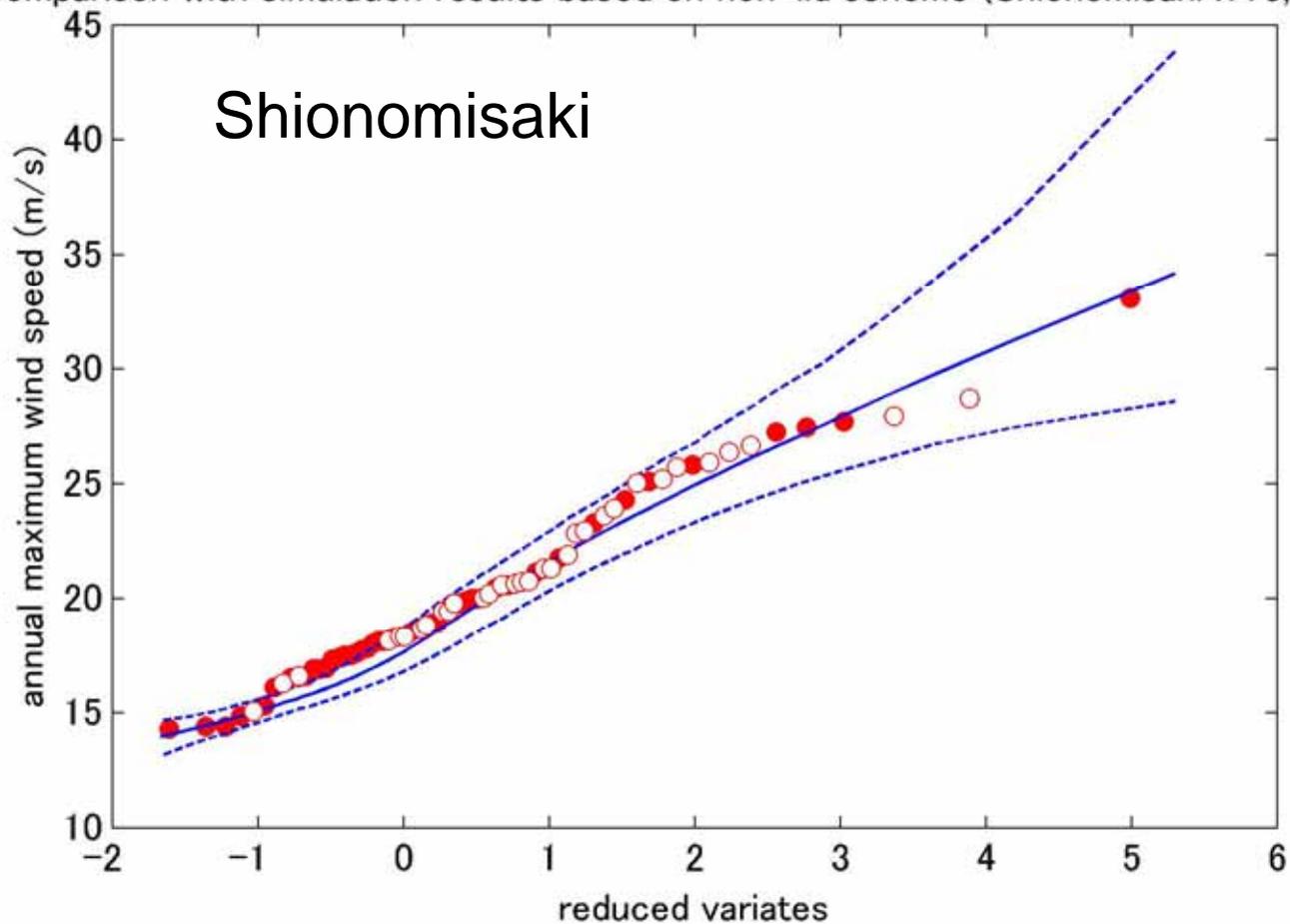


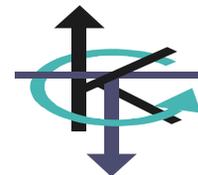
comparison with simulation results based on non-iid scheme (Kobe :770, M=74)



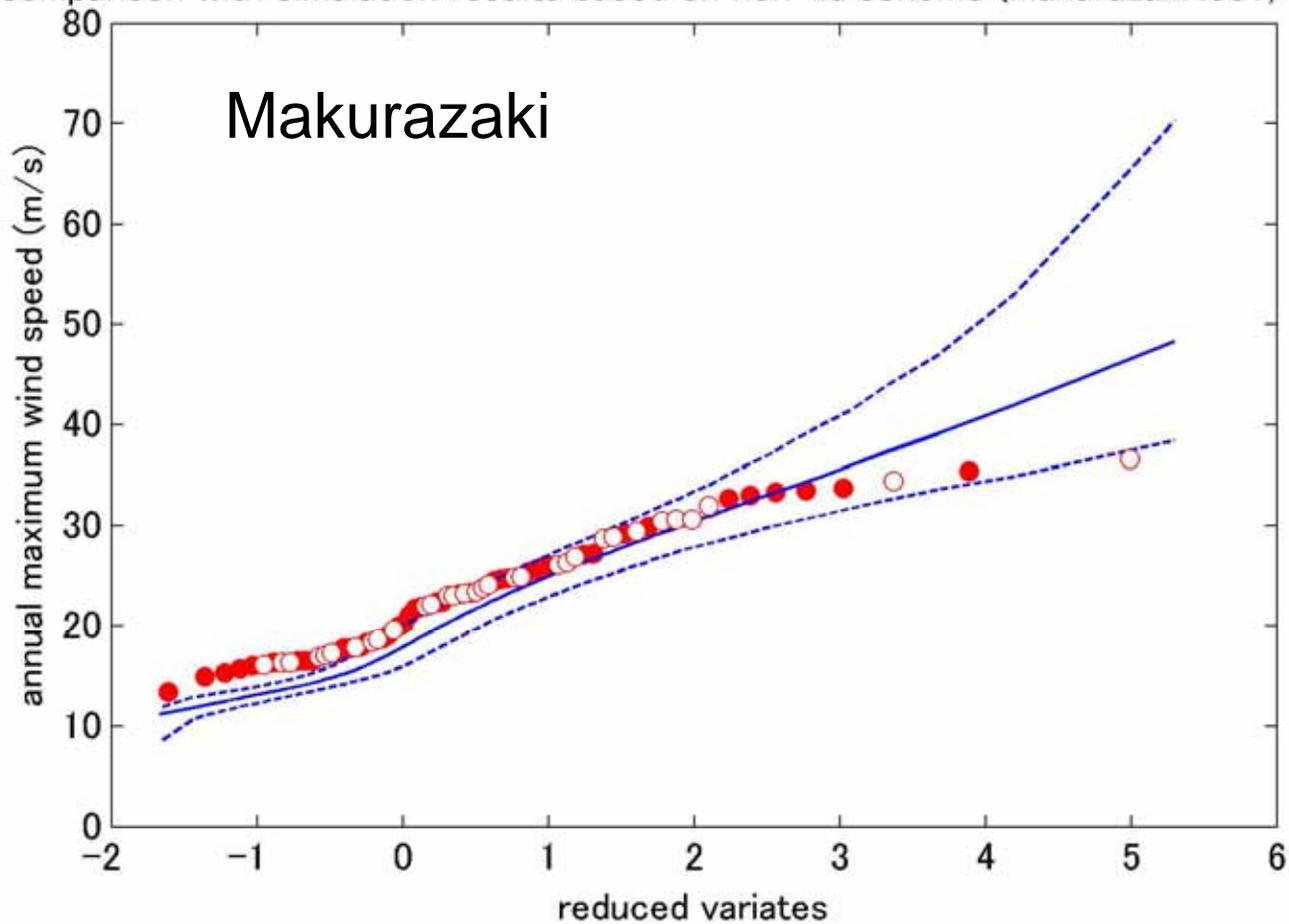


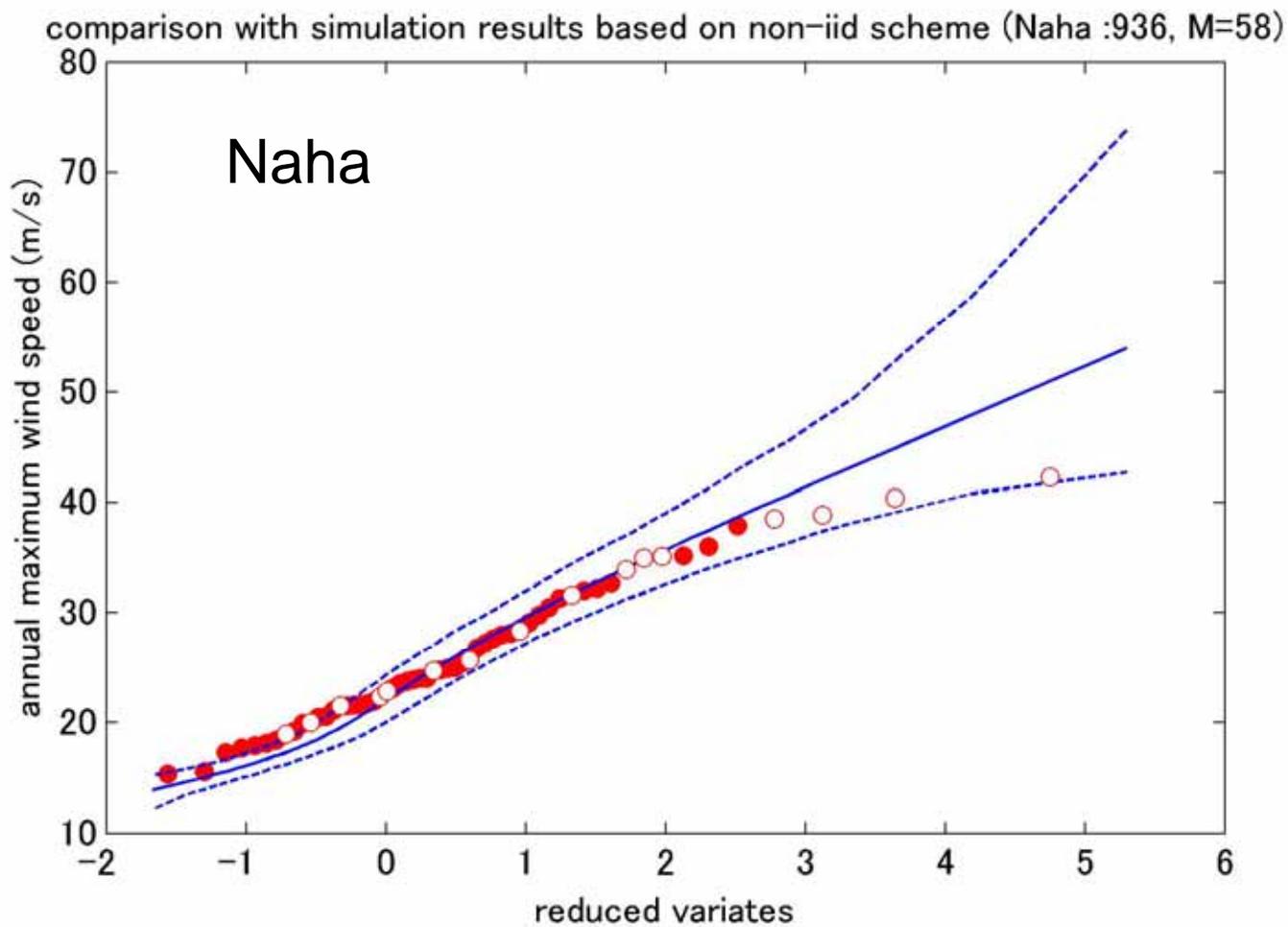
comparison with simulation results based on non-iid scheme (Shionomisaki :778, M=74)



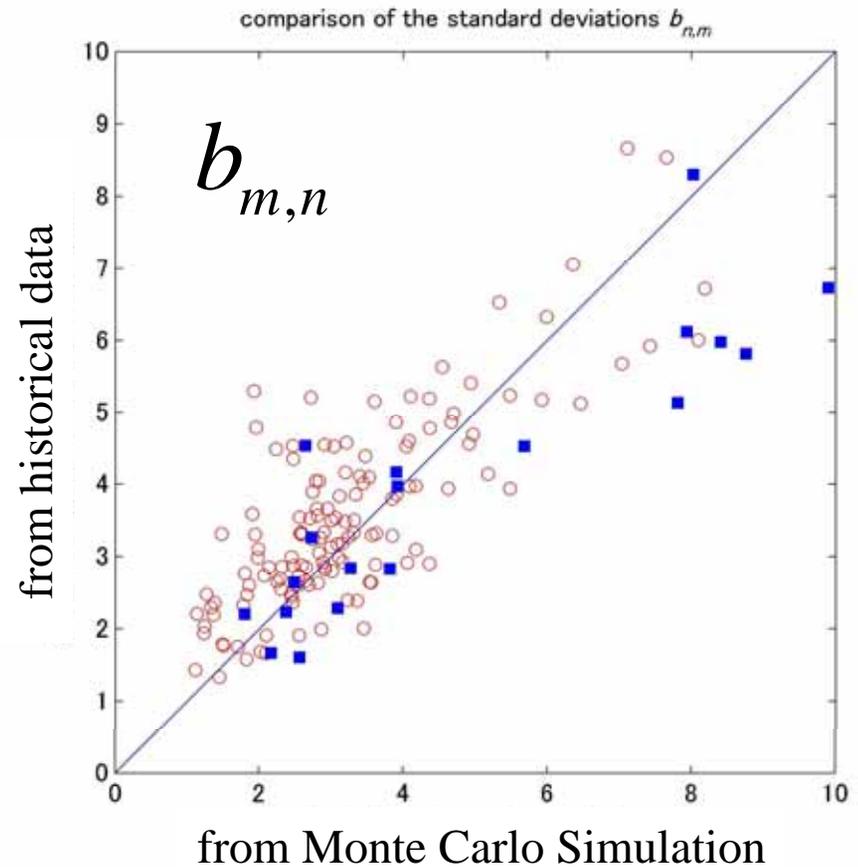
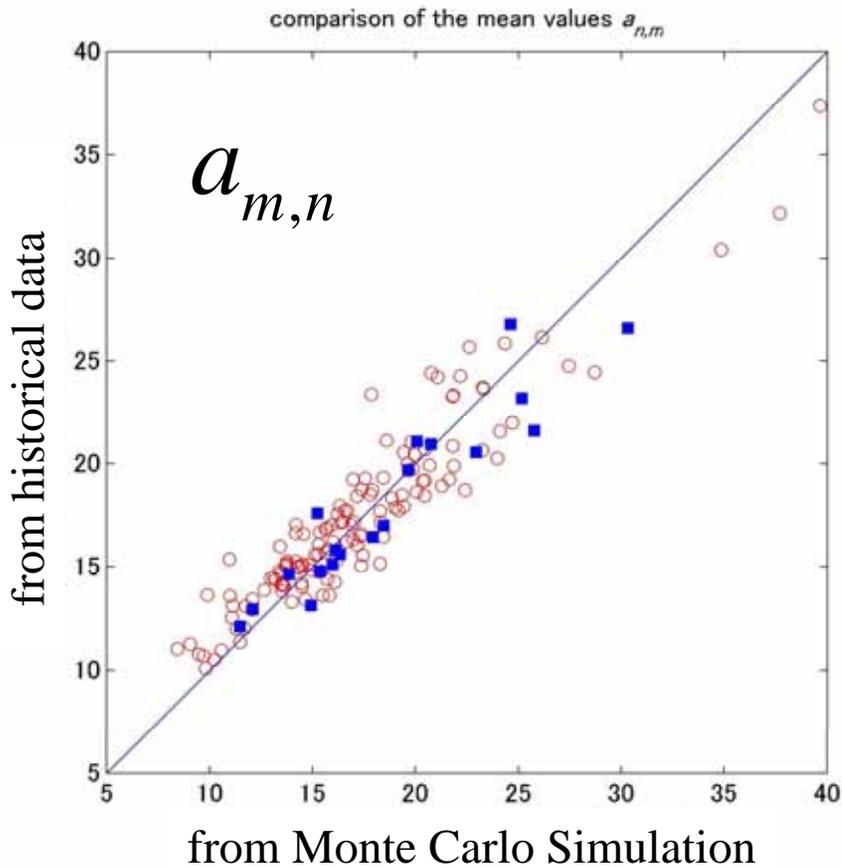
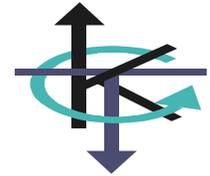


comparison with simulation results based on non-iid scheme (Makurazaki :831, M=74)





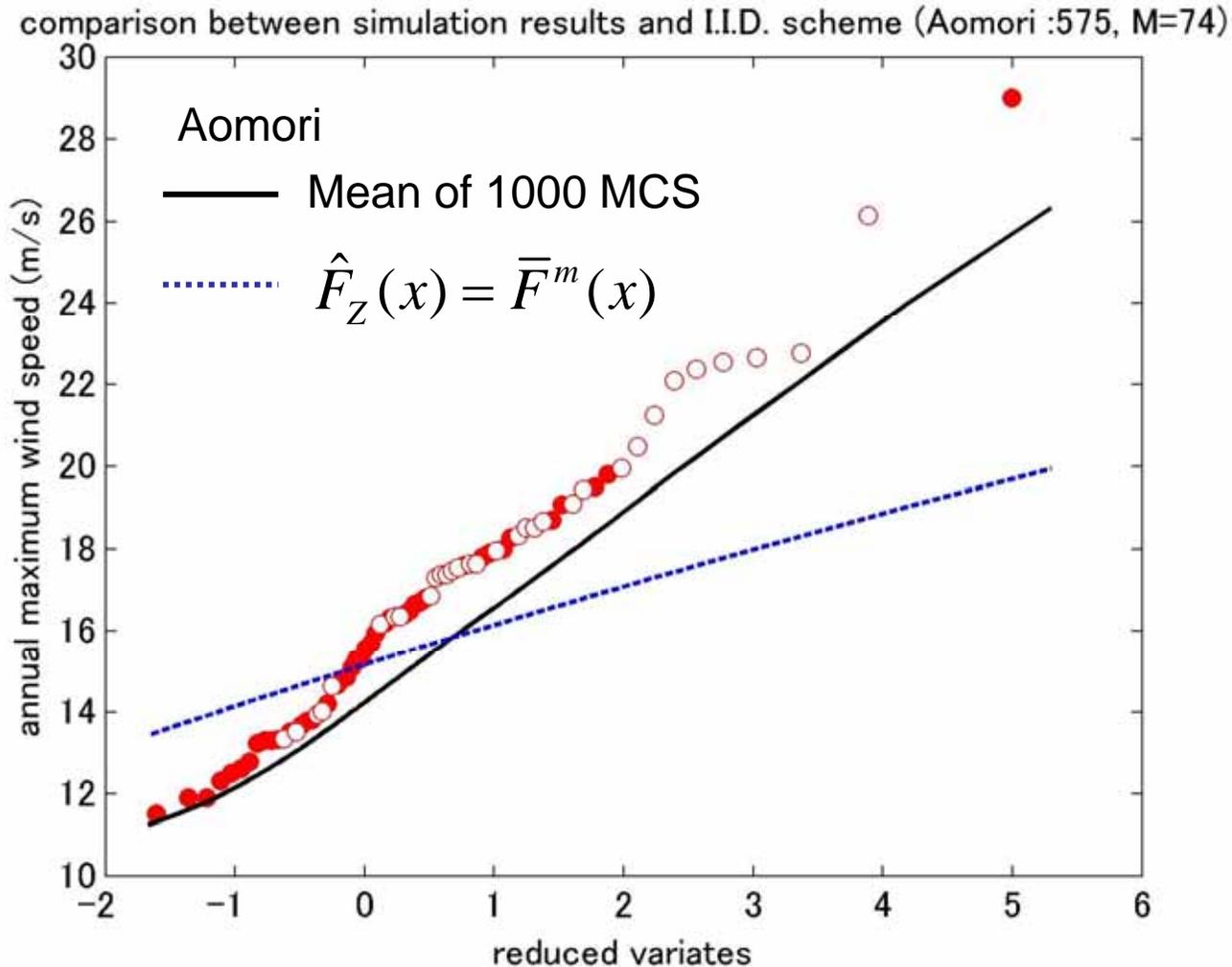
8) Comparison of the attraction coefficients from MCS and the historical records

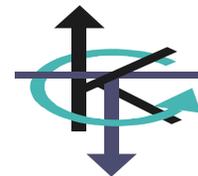


○ : $n > 50$ (136 sites), ■ : $n = 50$ (19 sites)

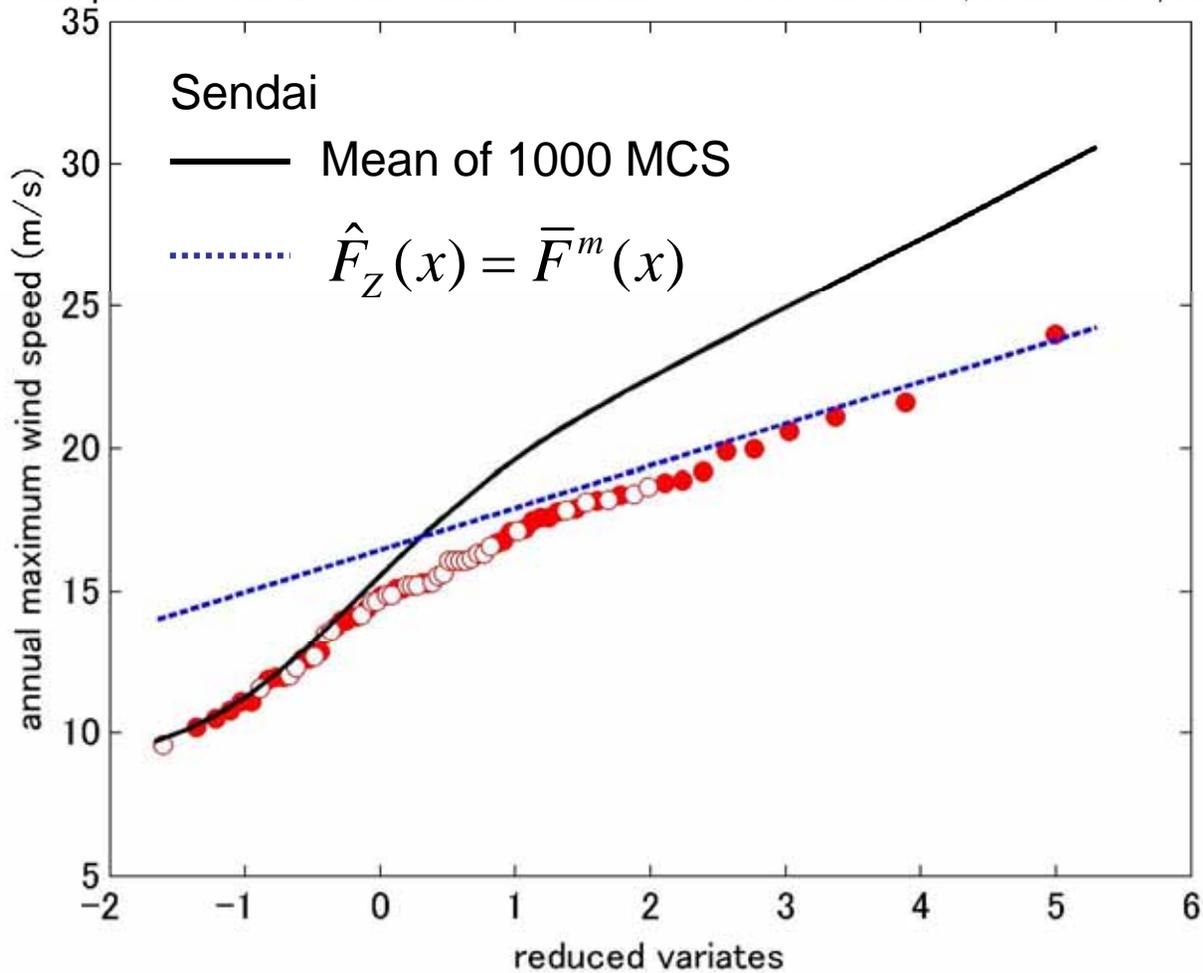
$$\lim_{n \rightarrow \infty} a_{m,n} = a_m, \quad \lim_{n \rightarrow \infty} b_{m,n} = b_m$$

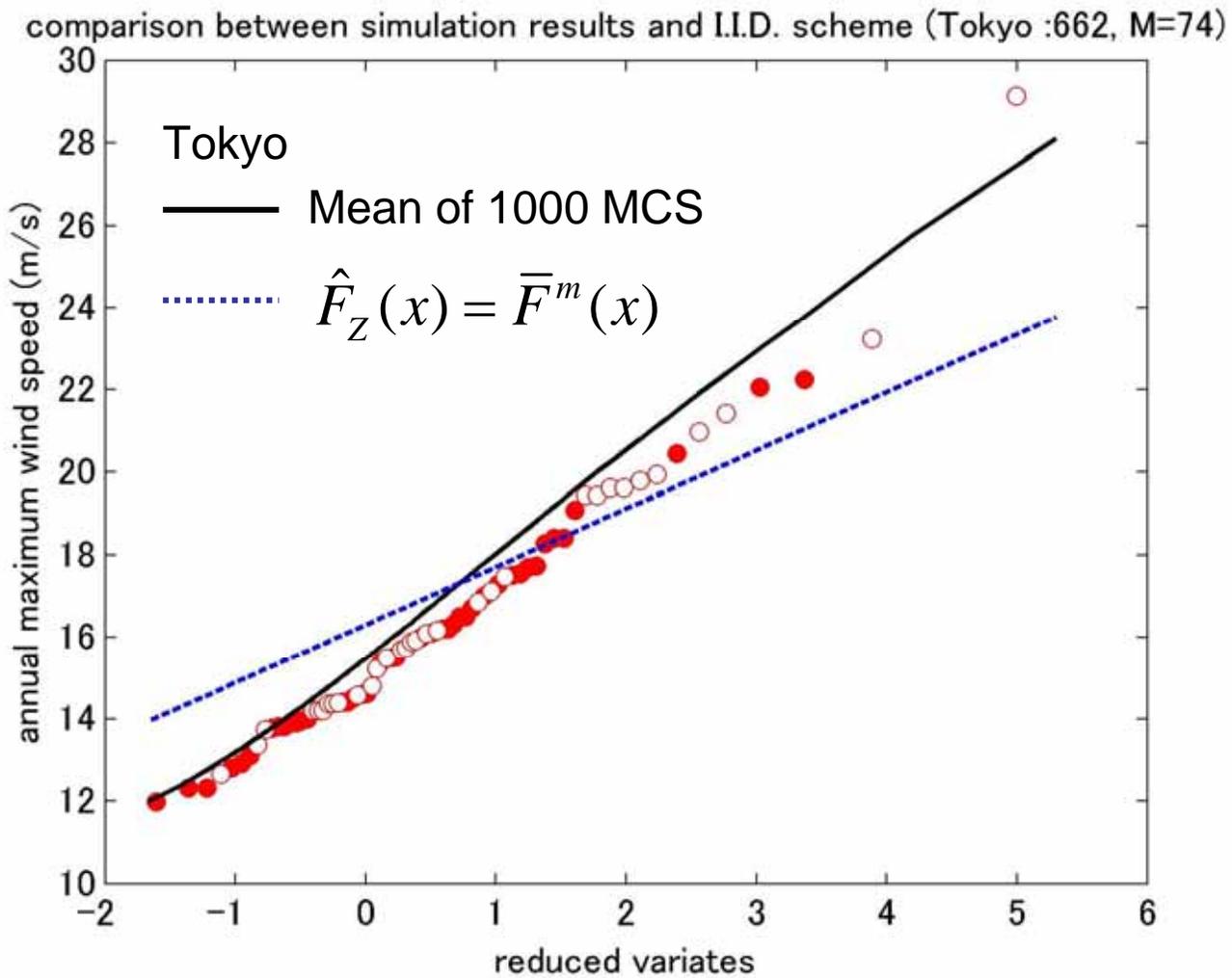
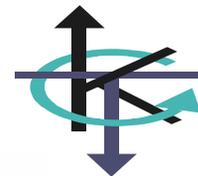
9) Defect of the alternative definition $\hat{F}_Z(x) = \bar{F}^m(x)$

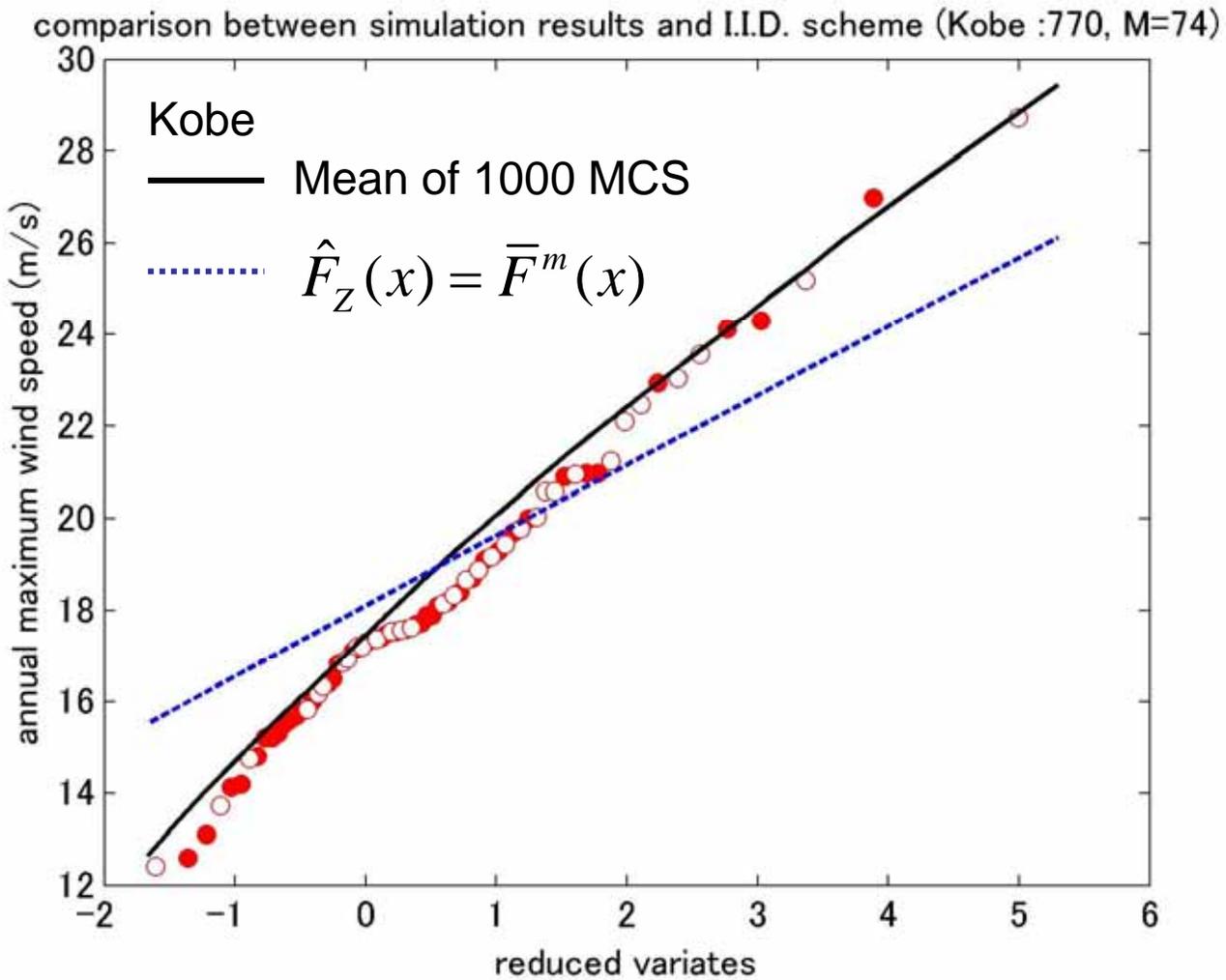


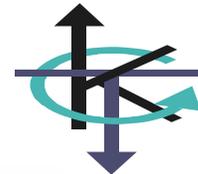


comparison between simulation results and I.I.D. scheme (Sendai :590, M=74)

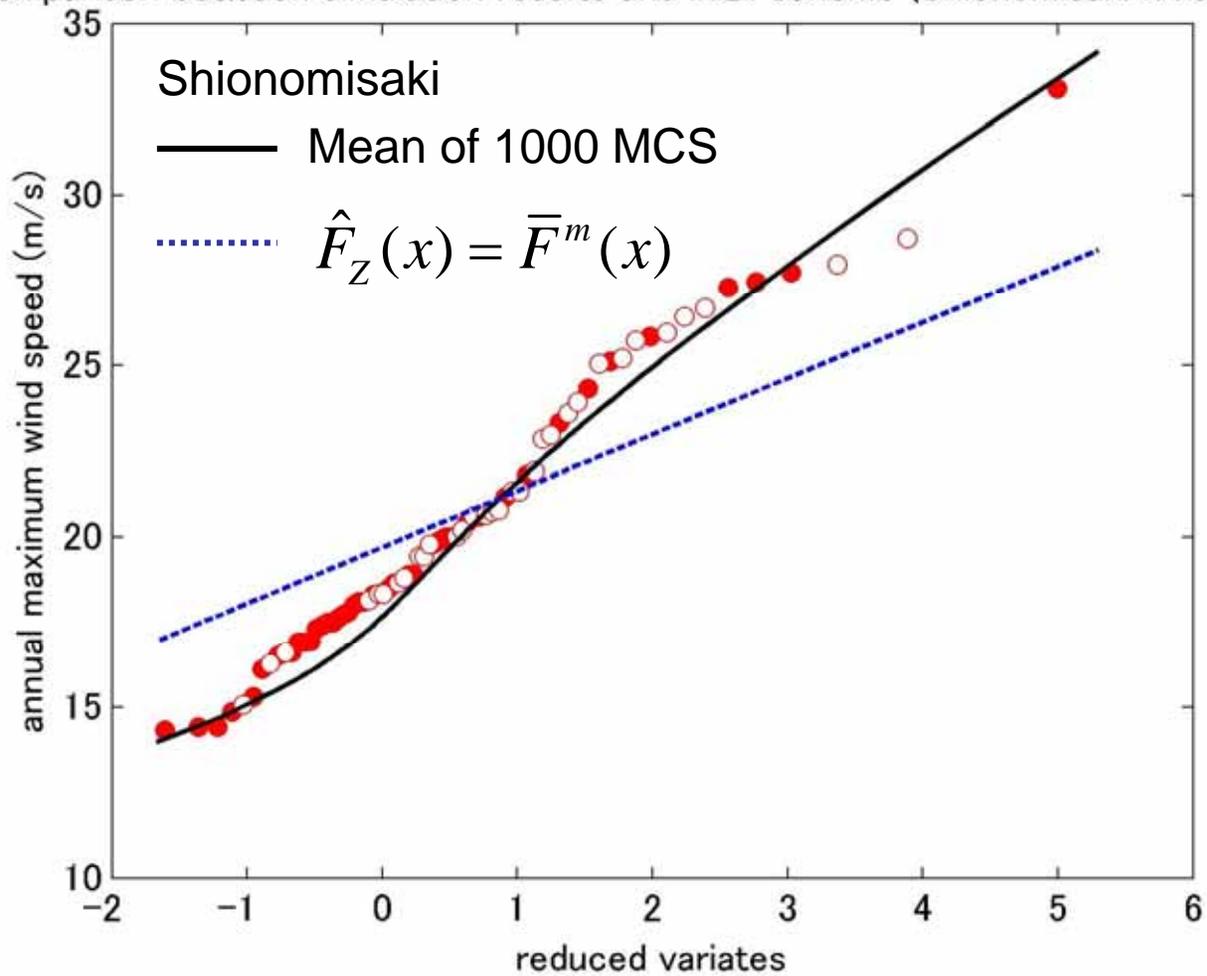


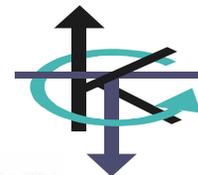




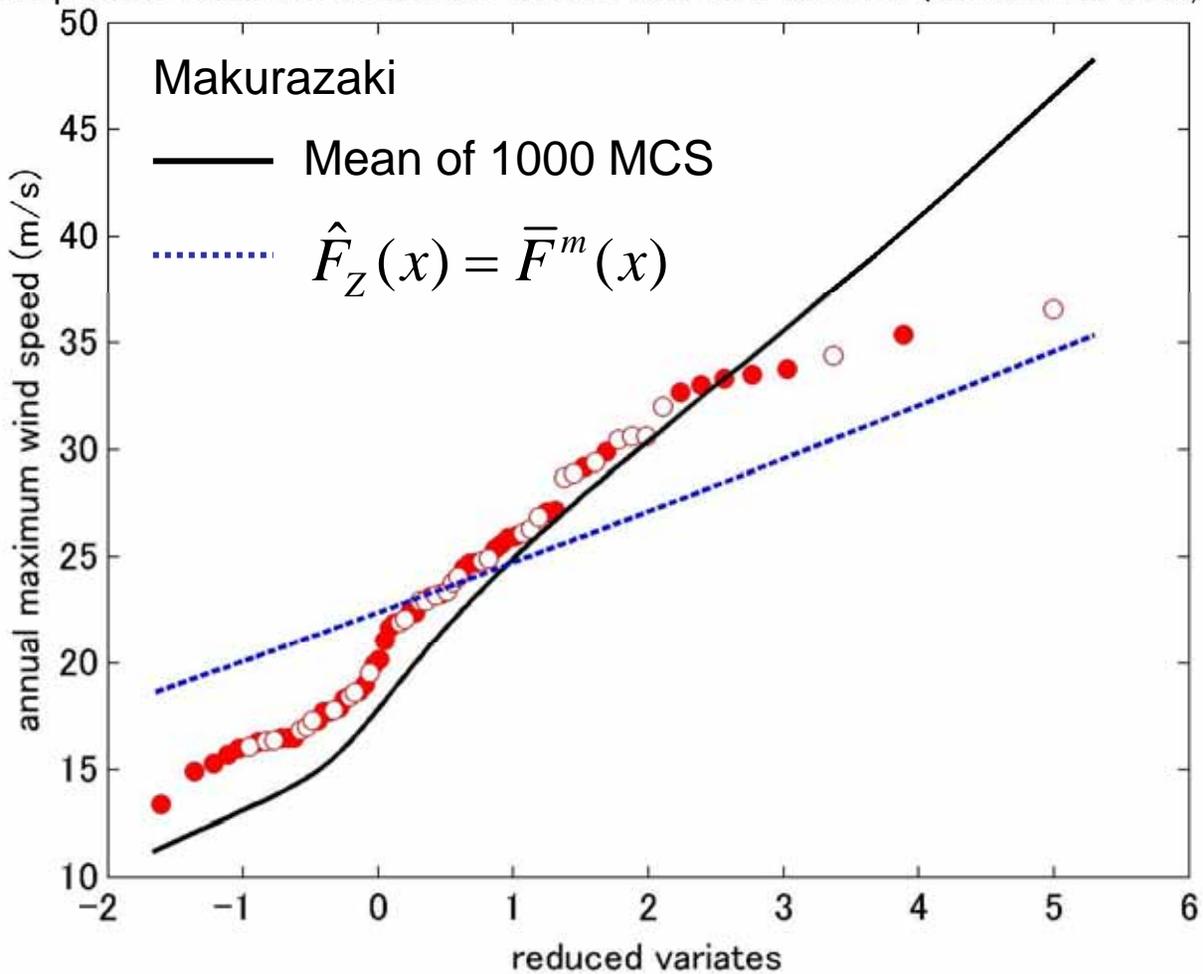


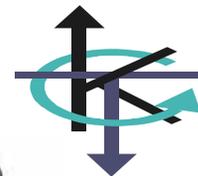
comparison between simulation results and I.I.D. scheme (Shionomisaki :778, M=74)



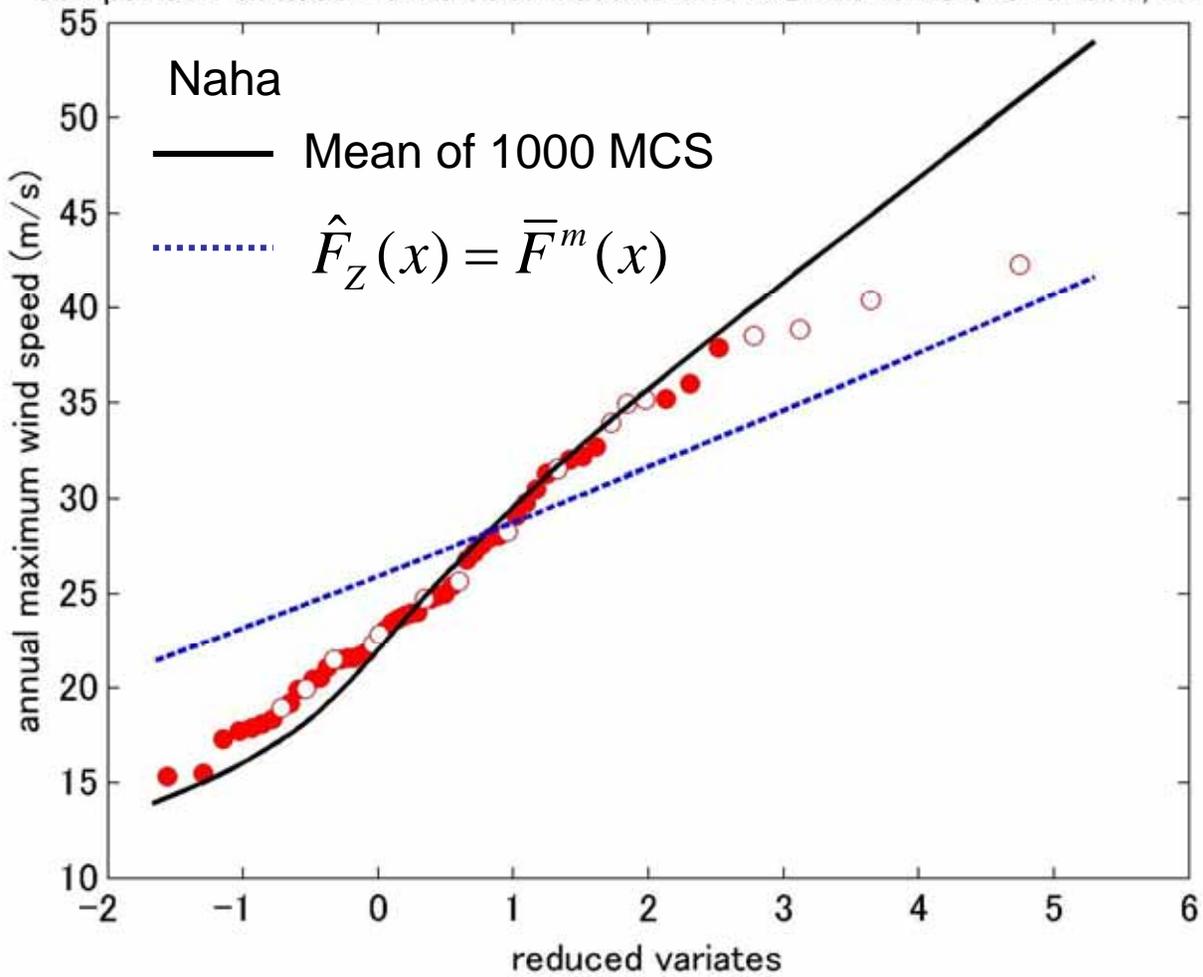


comparison between simulation results and I.I.D. scheme (Makurazaki :831, M=74)

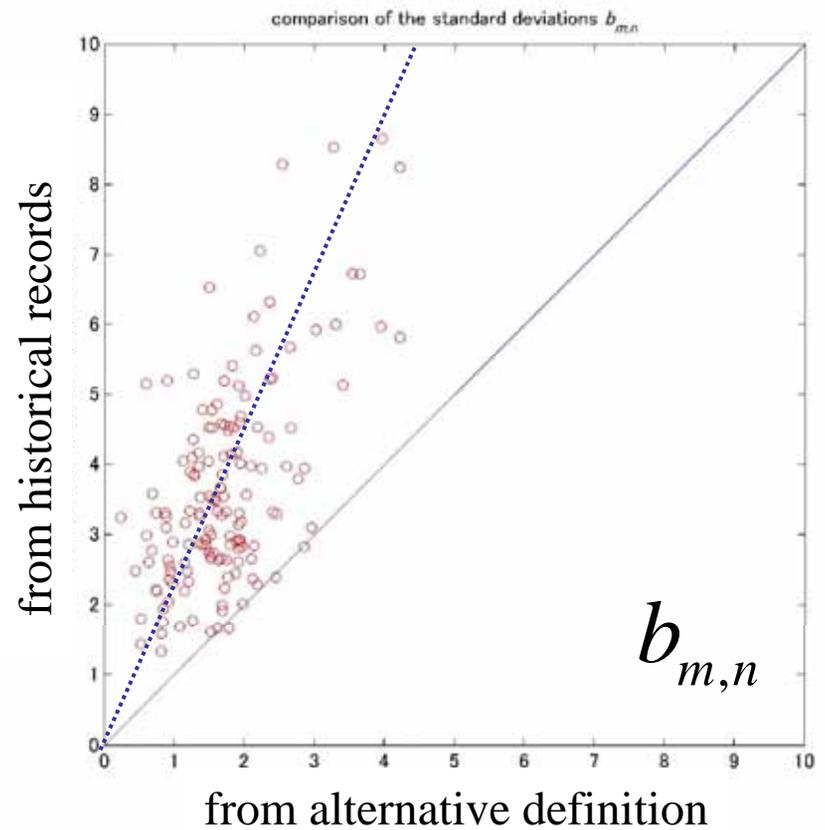
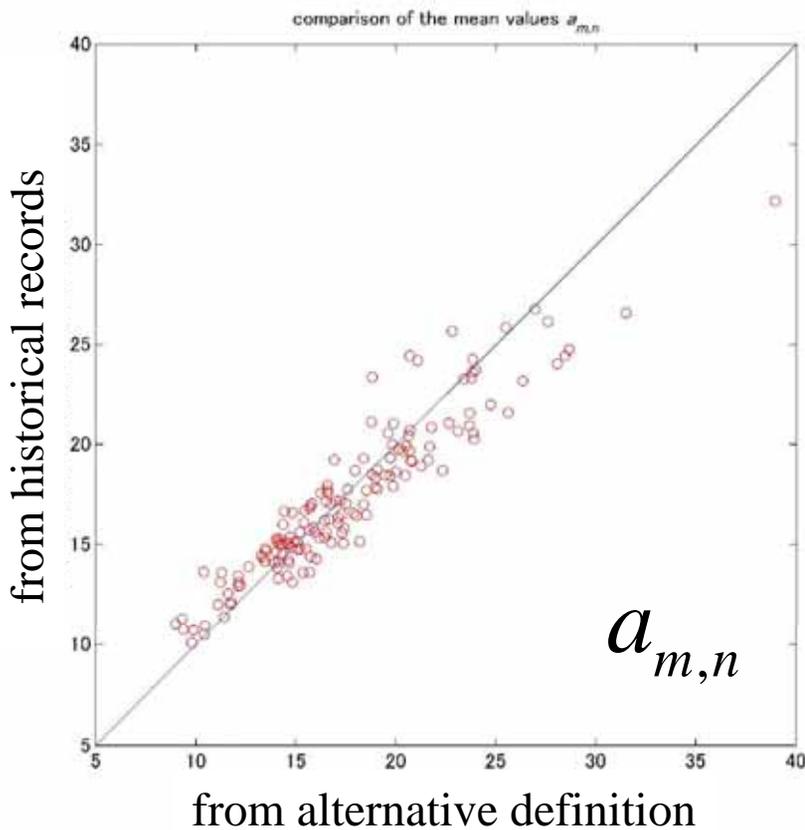
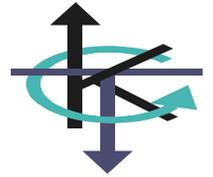




comparison between simulation results and I.I.D. scheme (Naha :936, M=58)



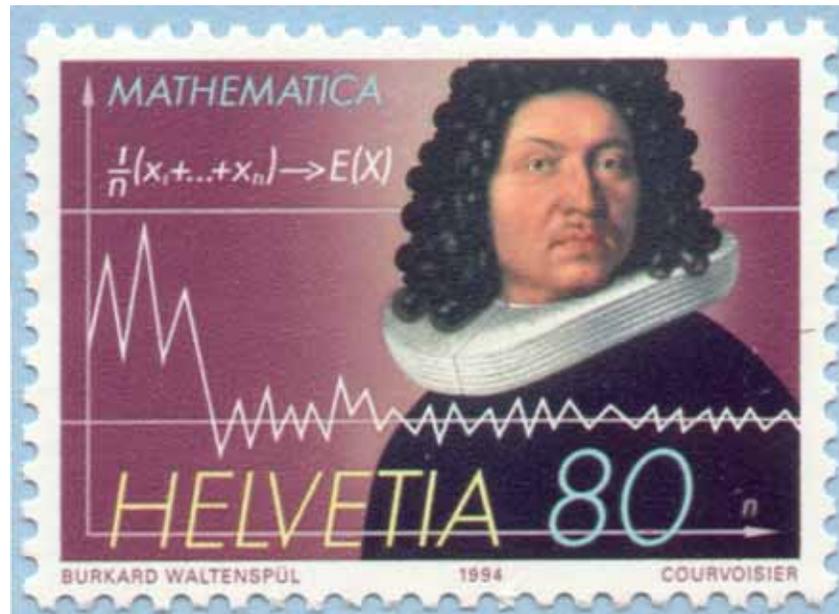
10) Comparison of the attraction coefficients from the alternative definition and the historical records



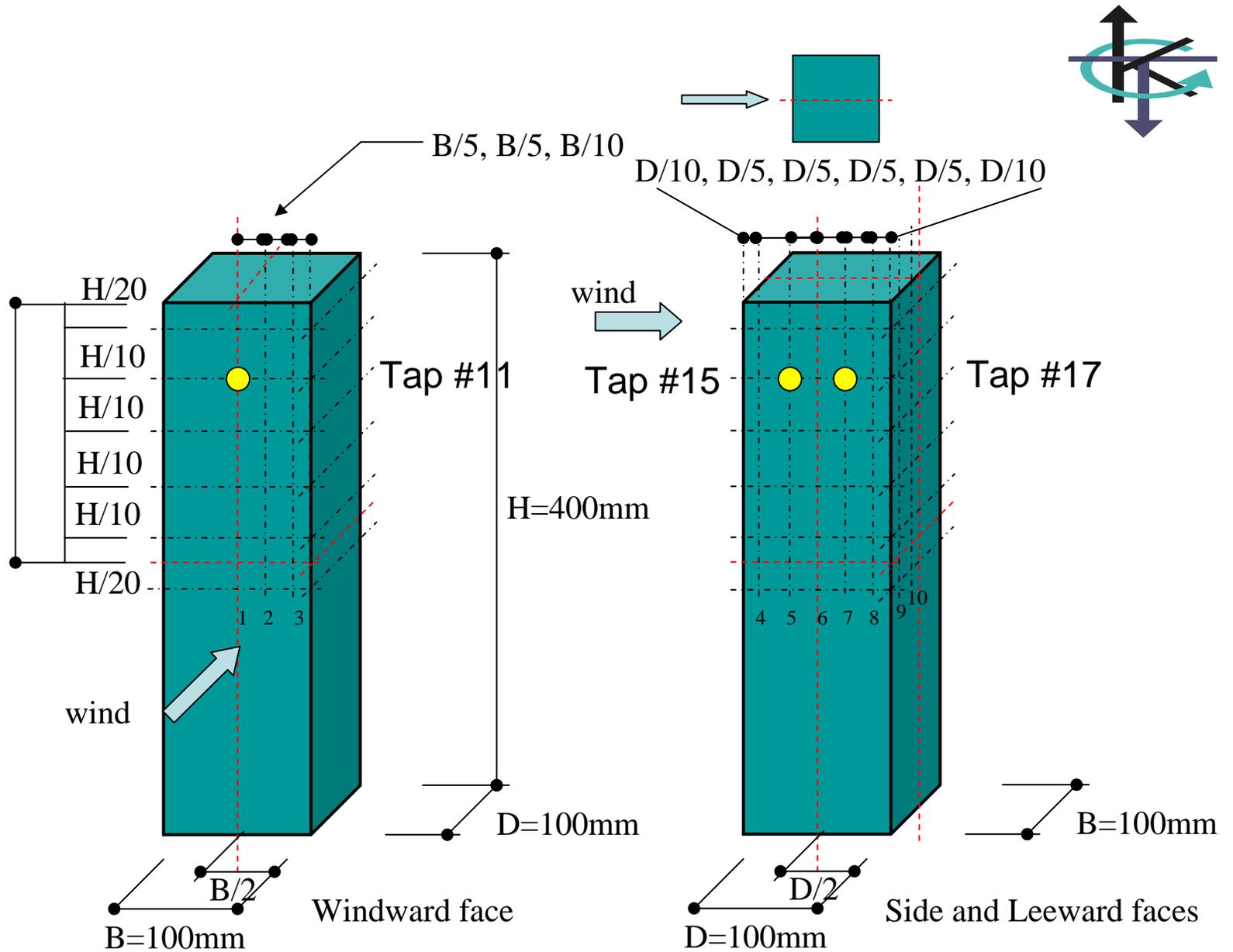
10 The cult of isolated statistics and The law of large number



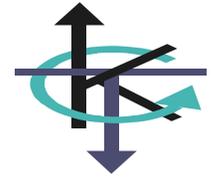
How many extreme values should be used to
estimate an extreme value distribution?
(case study for max/min pressure coefficients)*



* Choi & Kanda (2004), Stability of extreme quantile function estimation from relatively short records having different parent distributions, *Proc. 18th Natl. Symp. Wind Engr.*, p455~460 (in Japanese)

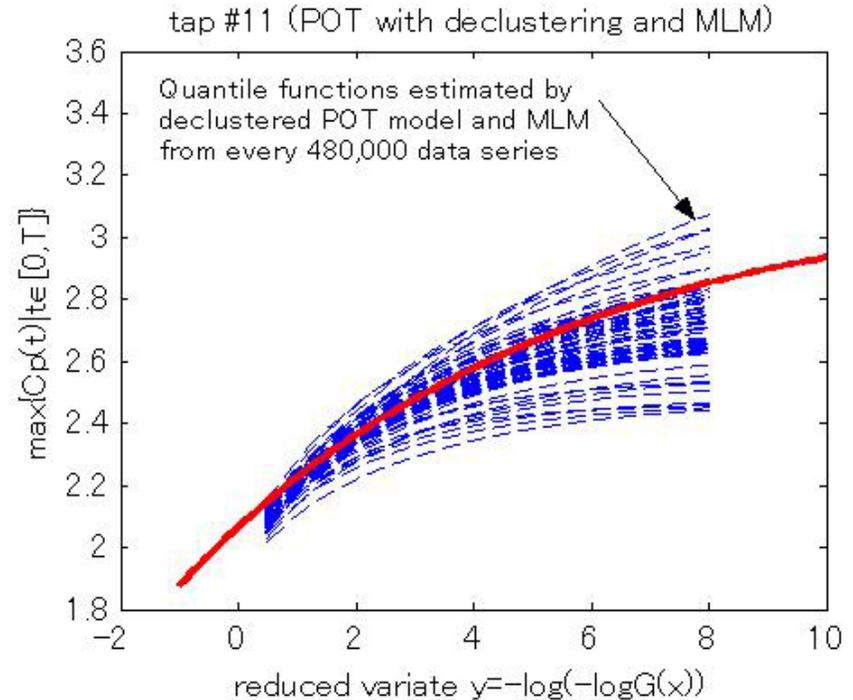
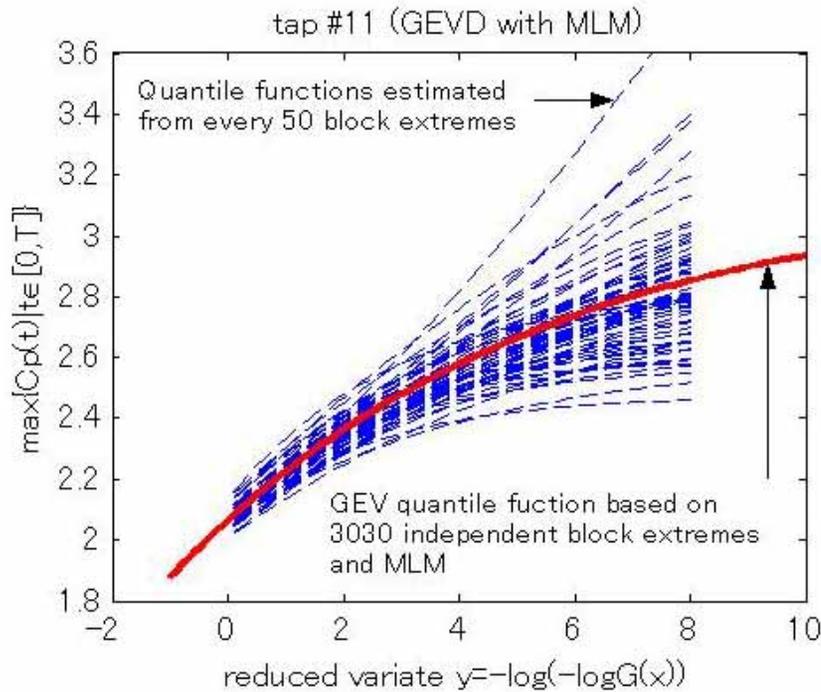


Which one is the best estimation?



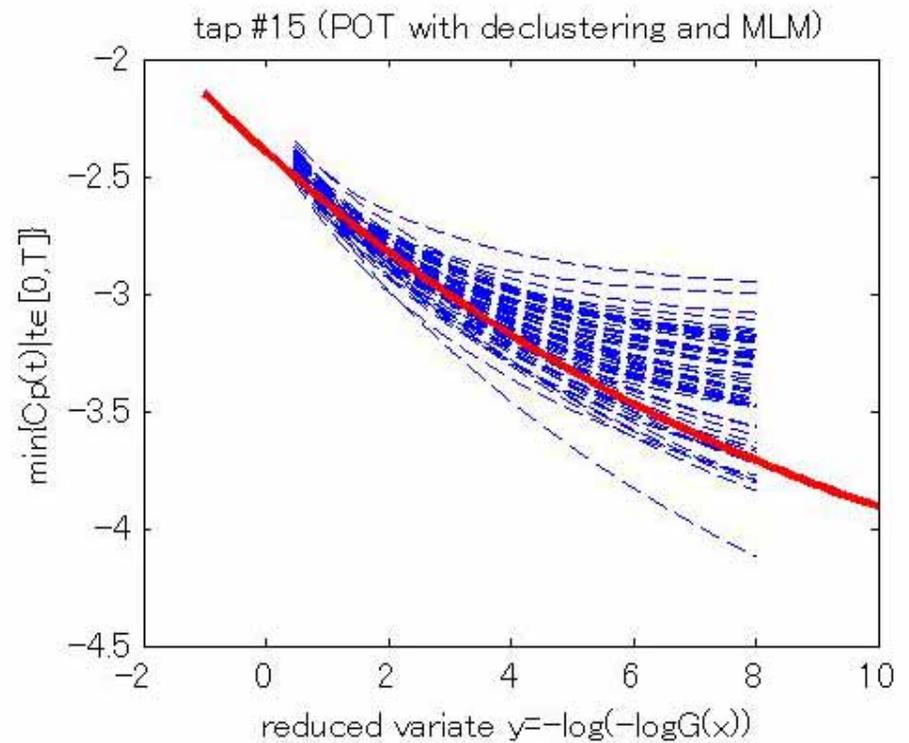
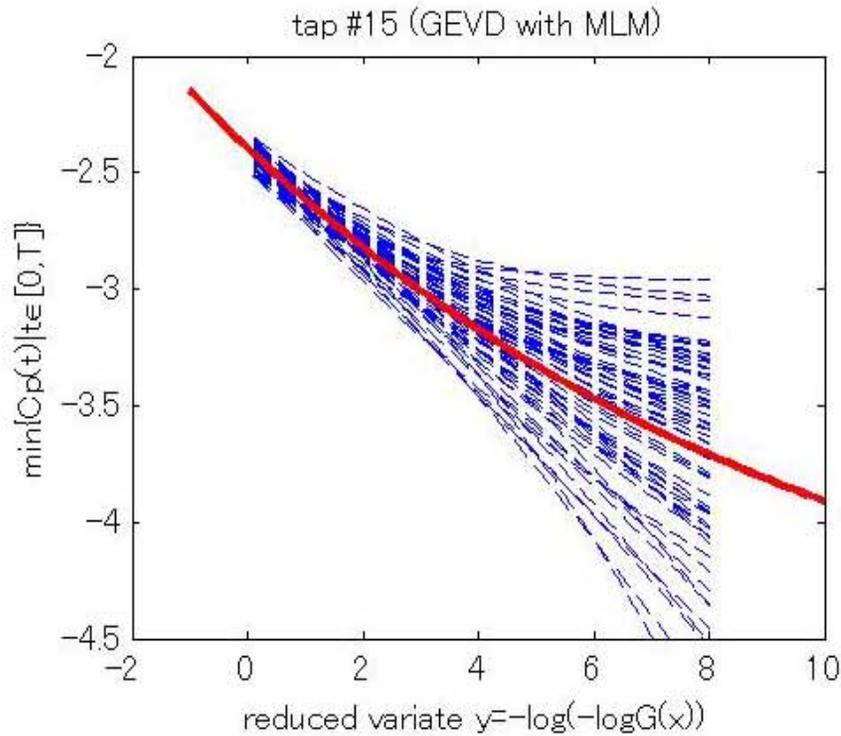
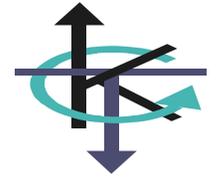
$$C_p(t) = \frac{p(t) - p_s}{1/2 \rho U_H^2}$$

$p(t)$: instant total pressure, p_s : static pressure
 ρ : air density, U_H : wind velocity at model height



* 50 blocks contain about 480,000 discrete data

Which one is the best estimation?



10 The cult of isolated statistics and The law of large number



We never be free from the law of large number.

The statistician and the scientists/technologist need to understand that models are necessarily simplifications of the system being modelled; that they are , an absolute sense, wrong; that they are certainly provisional, but nonetheless are useful and necessary for successful quantitative thinking.

from J.A. Nelder (1986), Statistics, Science and Technology – The address of the president, delivered to the Royal Statistical Society on Wednesday, April 16th, 1986, J. R. Statist. Soc. A 149(2), p109~121