



Statistical Analysis of Extreme Rainfall Events over Indiana, USA

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May 17, 2007

Background and Motivation

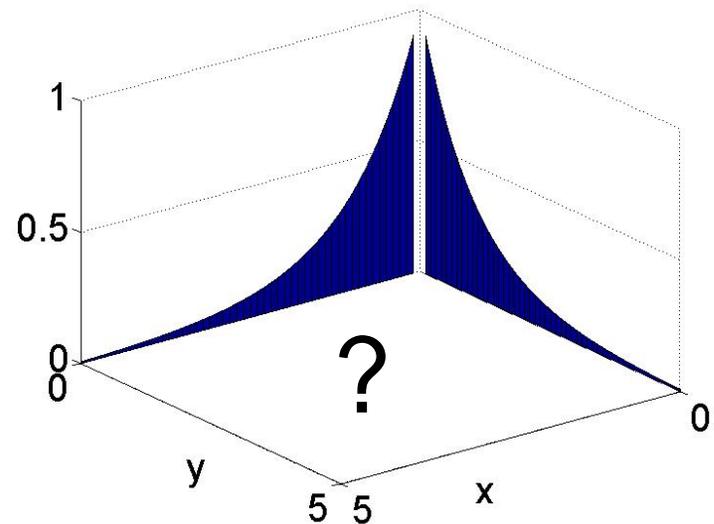


- Extreme rainfall behavior
 - Basis for hydrologic design
 - Conventionally analyzed only by “depth”
 - Pre-specified artificial duration (filter), *not* the real duration of extreme rainfall event
 - Hard to represent other rainfall characteristics, e.g. peak intensity
 - Definition of extreme event in multi-variate sense is not clear
 - Dependence exists between rainfall characteristics (e.g. volume(depth), duration, peak intensity)
 - Explore the use of copulas
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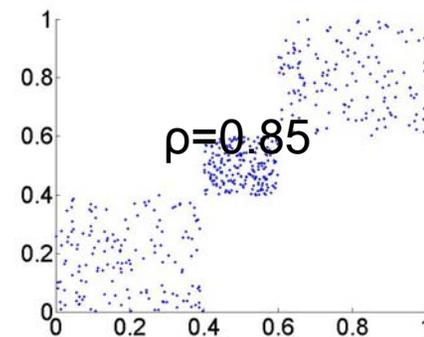
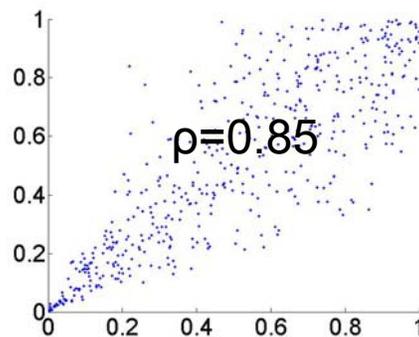
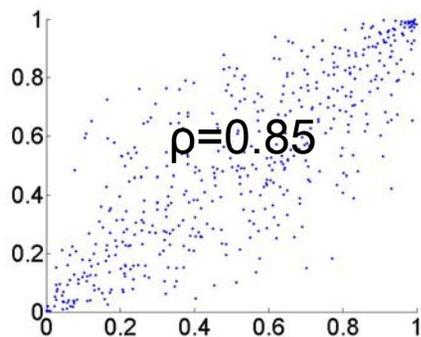
Difficulties in Constructing joint Distribution

- Given marginal distributions and correlation coefficient, can joint-distribution be constructed?

ex: exponential margins
=> Unlimited choices!!



- Correlation coefficient can not correctly describe association between variables



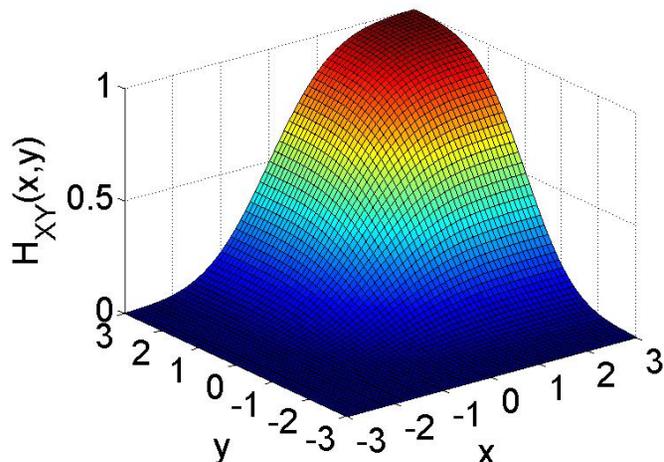
Introduction to Copulas

- A copula $C(u,v)$ is a function comprised of marginals $u=F_X(x)$ & $v=F_Y(y)$ from $[0,1] \times [0,1]$ to $[0,1]$.
 - Sklar (1959) showed that for continuous marginals u and v , there exists a unique copula C such that

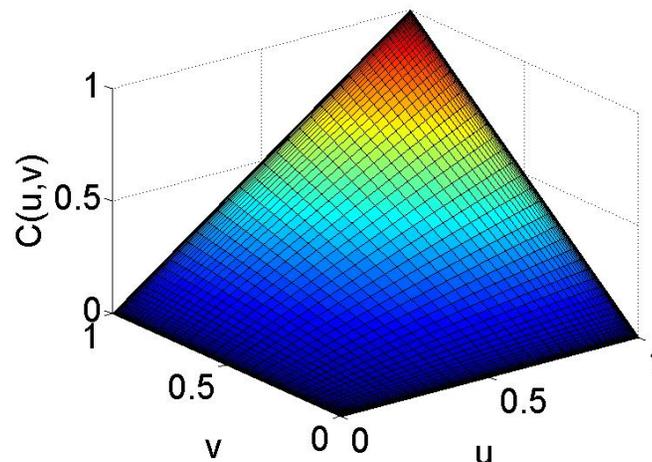
$$H_{XY}(x, y) = C_{UV}(F_X(x), F_Y(y)) = C_{UV}(u, v)$$

- Transformation from $[-\infty, \infty]^2$ to $[0,1]^2$

bivariate Gaussian distribution, $\rho = 0.1$

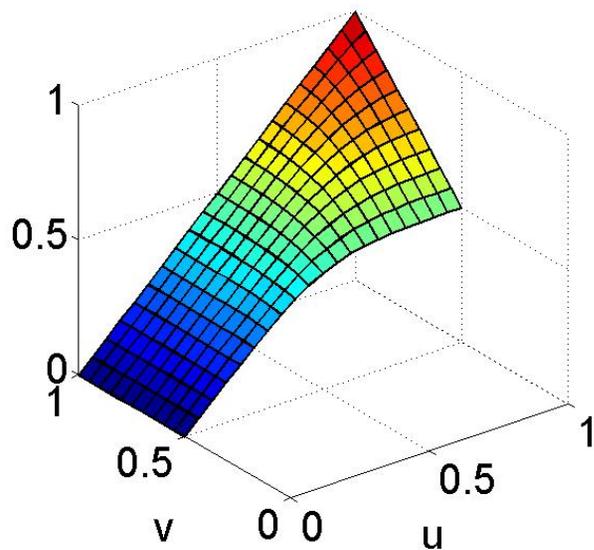


bivariate Gaussian distribution, $\rho = 0.1$

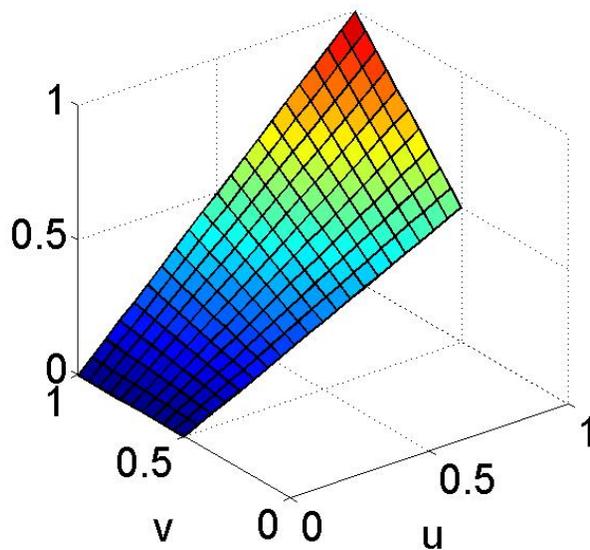


- Provides a complete description of dependence structure

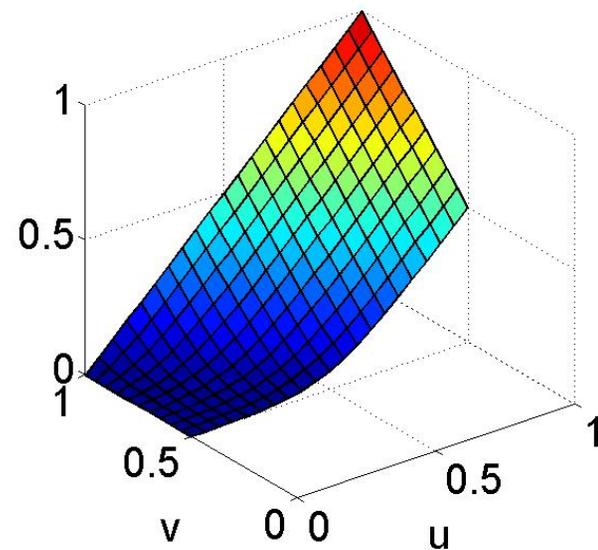
Frank family, $\theta=10$



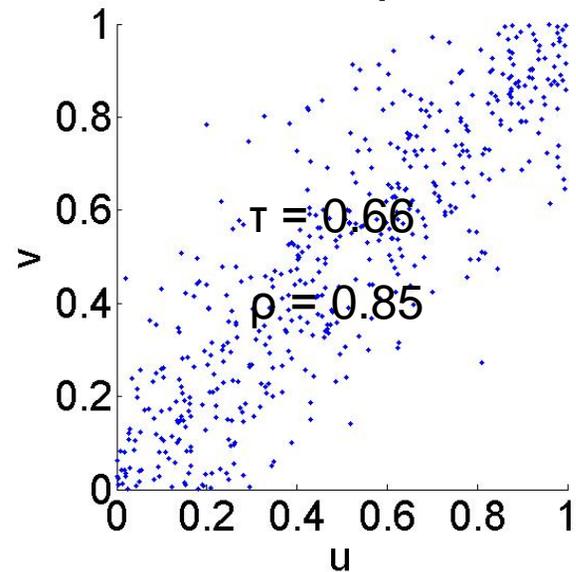
Frank family, $\theta=0.01$



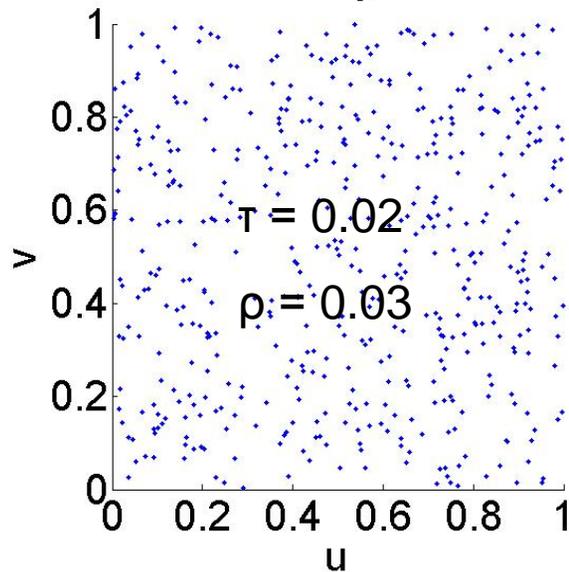
Frank family, $\theta=-10$



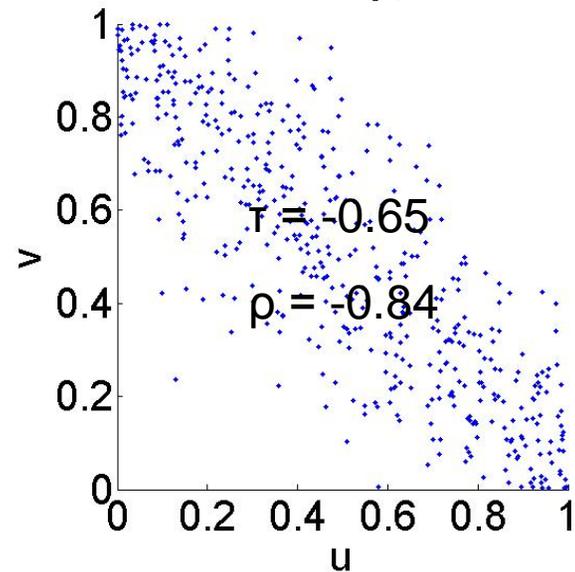
Frank family, $\theta=10$



Frank family, $\theta=0.01$



Frank family, $\theta=-10$



Applications of Copulas in Hydrology

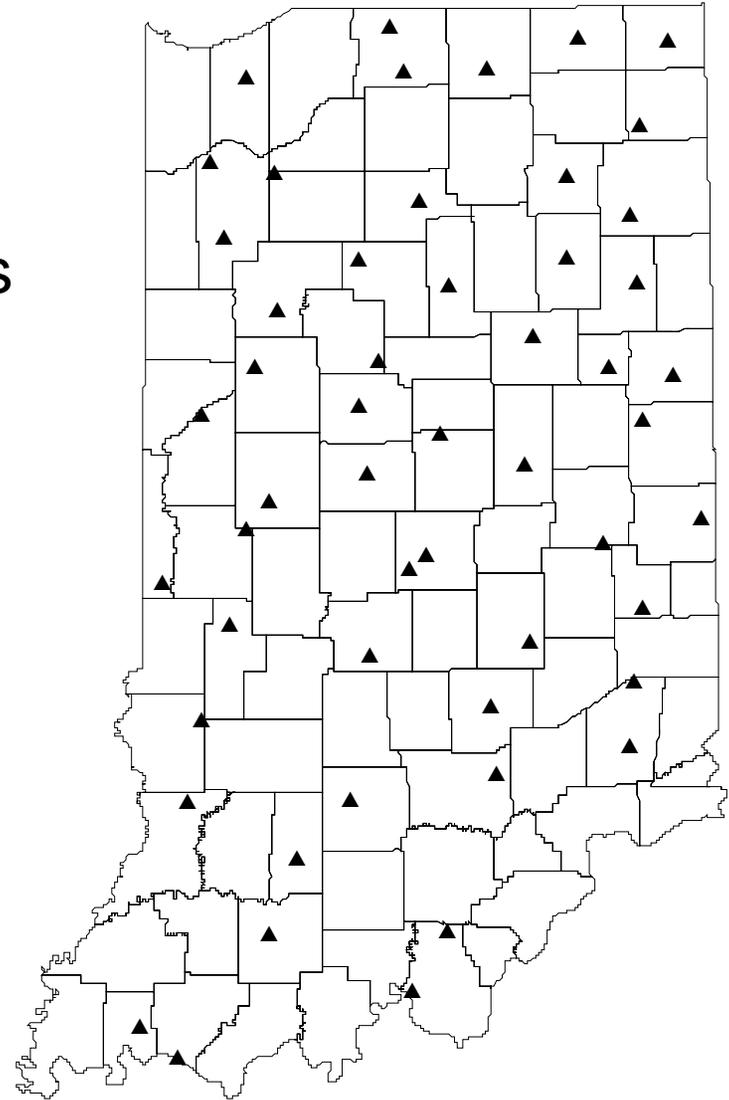


- Flood frequency analysis
 - Favre *et al.* (2004), De Michele *et al.* (2005), Grimaldi and Serinaldi (2006), Zhang and Singh (2006)
 - Return period assessment using bivariate model
 - Salvadori and De Michele (2004)
 - Probabilistic structure of storm surface runoff
 - Kao and Govindaraju (2007)
 - Rainfall frequency analysis
 - De Michele and Salvadori (2003, 2006), Grimaldi and Serinaldi (2006), Zhang and Singh (2006)
 - Unanswered questions in rainfall frequency analysis
 - Data used for analysis may not be sufficient
 - Definition of “extreme events” in multi-variate sense?
 - Can results be applied for a large region?
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Data Source & Study Area

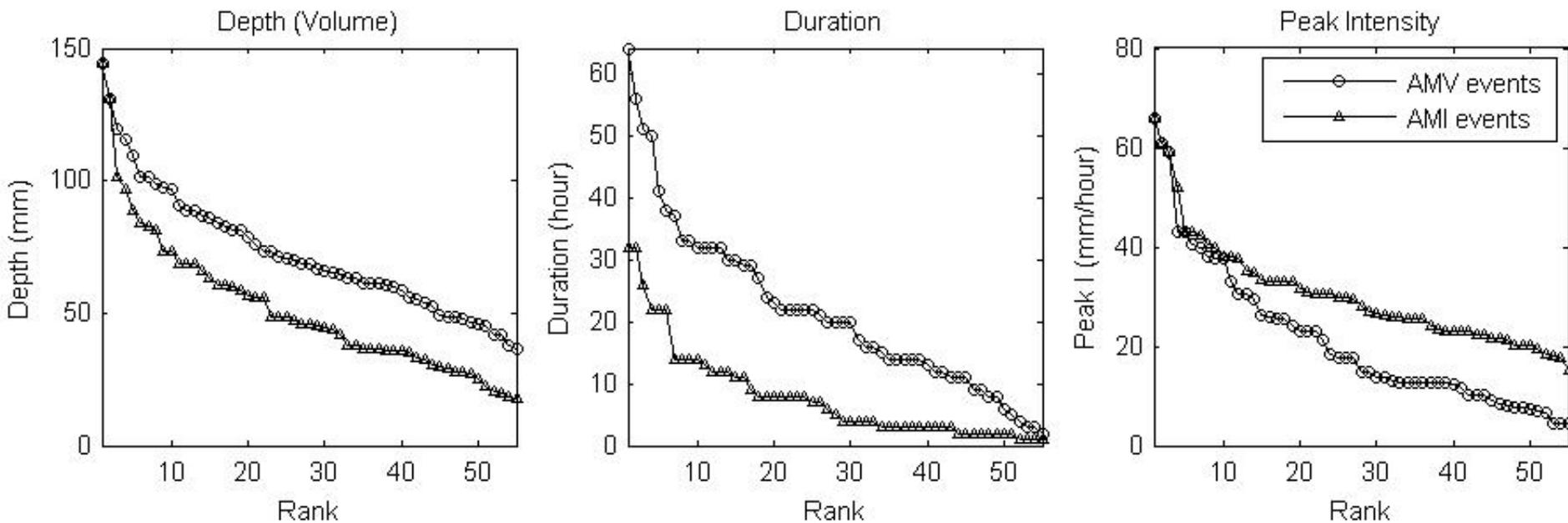


- Nation Climate Data Center, Hourly Precipitation Dataset (NCDC, TD 3240 dataset)
- 53 Co-operative Rainfall Stations in Indiana with record length greater than 50 years
- Minimum rainfall hiatus: 6 hours
- About 4800 events per station
- Selected variables for analysis:
 - Depth (volume), P (mm)
 - Duration, D (hour)
 - Peak Intensity, I (mm/hour)
- Marginals:
 - $u=F_P(p)$, $v=F_D(d)$, $w=F_I(i)$



Definitions of Extreme Events

- Hydrologic designs are usually governed by depth (volume) or peak intensity
- Annual maximum volume (AMV) events
 - Longer duration
- Annual maximum peak intensity (AMI) events
 - Shorter duration

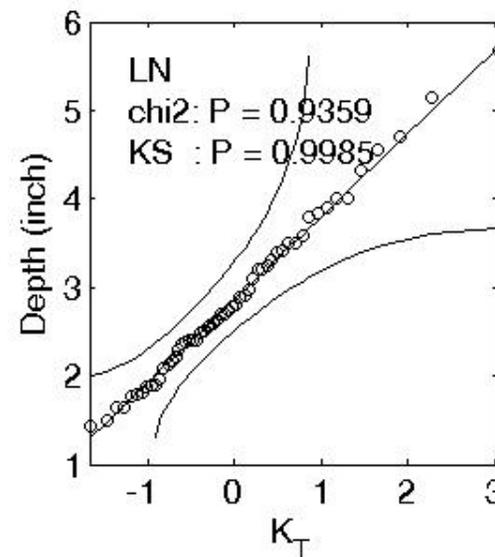
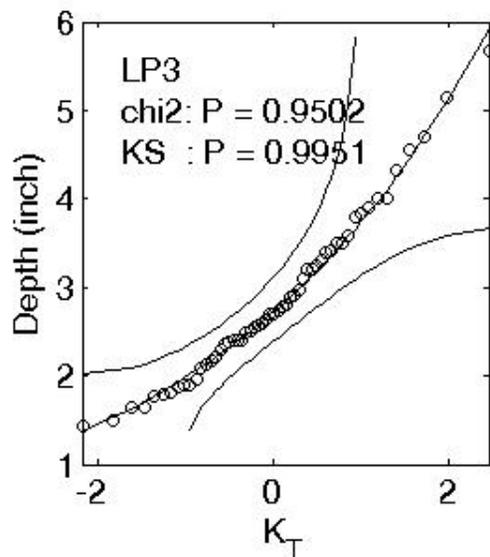
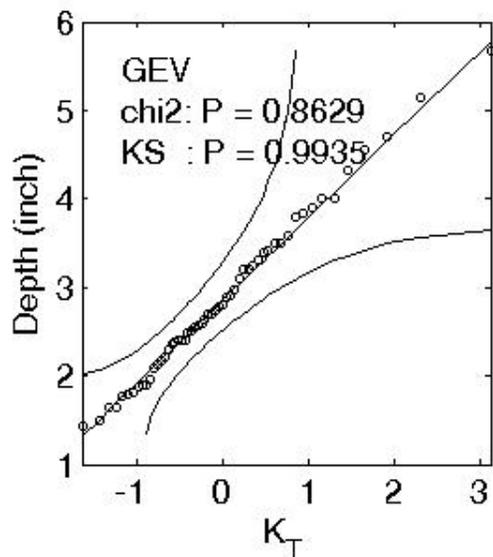
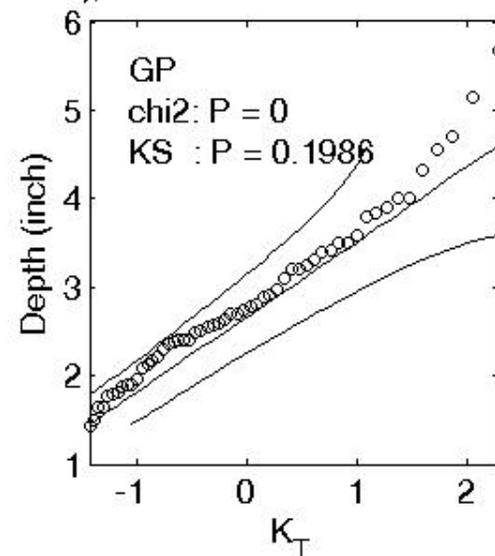
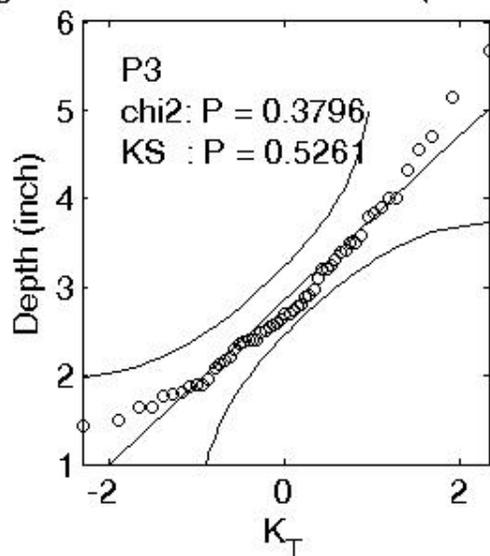
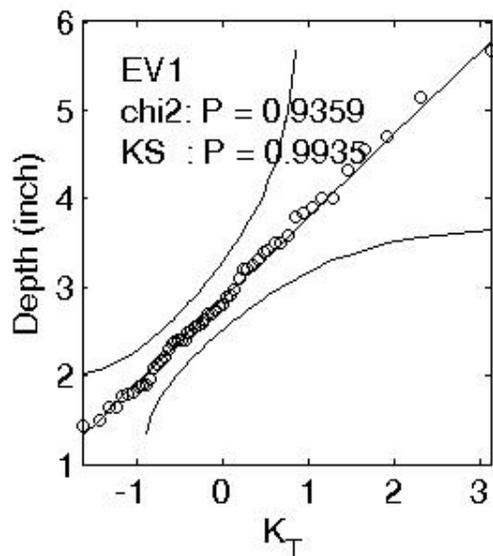


Analysis of Marginal Distributions (I)



- Candidate distributions
 - Extreme value type I (EV1)
 - Generalized extreme value (GEV)
 - Pearson type III (P3)
 - Log-Pearson type III (LP3)
 - Generalized Pareto (GP)
 - Log-normal (LN)
 - Parameters estimated primarily by maximum likelihood (ML) or method of moments (MOM)
 - Gringorton formula for empirical probabilities
 - Chi-square and Kolmogorov-Smirnov (KS) test with 10% significance level
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Identification of marginal distributions of volume (AMV events), Station 120132



Analysis of Marginal Distributions (II)



AMV events	Rejection rate (%) of Chi-square test						Rejection rate (%) of KS test					
	EV1	GEV	P3	LP3	GP	LN	EV1	GEV	P3	LP3	GP	LN
Depth, P	13.2	17.0	41.5	17.0	100	13.2	0.0	0.0	7.5	0.0	52.8	0.0
Duration, D	13.2	15.1	24.5	37.7	100	22.6	1.9	0.0	7.5	0.0	22.6	0.0
Intensity, I	15.1	17.0	45.3	20.8	100	11.3	0.0	0.0	1.9	0.0	54.7	0.0

AMI events	Rejection rate (%) of Chi-square test						Rejection rate (%) of KS test					
	EV1	GEV	P3	LP3	GP	LN	EV1	GEV	P3	LP3	GP	LN
Depth, P	5.7	3.8	62.3	3.8	100	1.9	0.0	0.0	11.3	0.0	45.3	0.0
Duration, D	60.4	39.6	88.7	37.7	100	28.3	15.1	0.0	45.3	0.0	45.3	0.0
Intensity, I	15.1	15.1	34.0	18.9	100	15.1	0.0	0.0	5.7	0.0	71.7	0.0

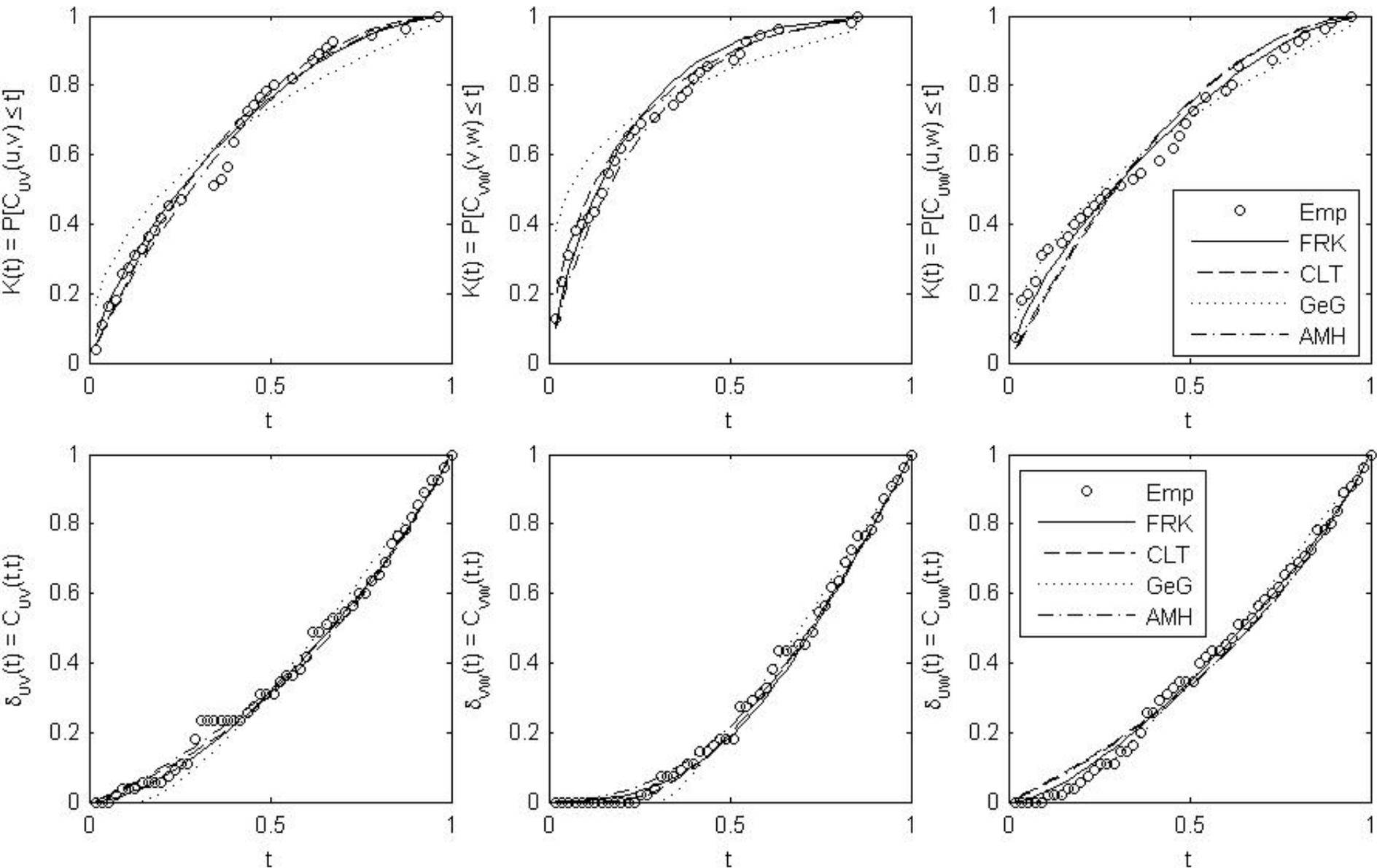
- EV1, GEV, LP3, LN provided better fit. GP provided the worst.
- Fitting for duration of AMI events did not yield very good result due to the limited temporal precision (hour)
- EV1 and LN could be recommended for use

Analysis of Dependence Structure (I)



- Candidate Archimedean copulas
 - Frank family
 - Clayton family
 - Genest-Ghoudi family
 - Ali-Mikhail-Haq family
 - Non-parametric procedure for estimating dependence parameter
 - Examination of Goodness-of-fit
 - Distribution function $K_C(t) = P[C(u,v) \leq t]$
 - Diagonal section of copulas $\delta(t) = C(t,t)$
 - Multidimensional KS test (Saunders and Laud, 1980)
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Assessment of Copula Performance



Analysis of Dependence Structure (II)



- Statistics of Kendall's tau

	τ_{PD}		τ_{DI}		τ_{PI}	
	mean	stdev	mean	stdev	mean	stdev
AMV events	0.183	0.084	-0.370	0.068	0.260	0.097
AMI events	0.407	0.070	-0.011	0.096	0.405	0.070

- The distribution function $K_C(t)$ provides the strictest examination of copulas
- Clayton and Ali-Mikhail-Haq families performed well for positive dependence cases (C_{UV} and C_{UW})
- Frank family of Archimedean copulas
 - performed well for both positive and negative dependence
 - passed the KS test for entire Indiana at the 10% significant level
 - recommended for use in practice

Construct Joint Distribution via Copulas



- Bivariate stochastic models

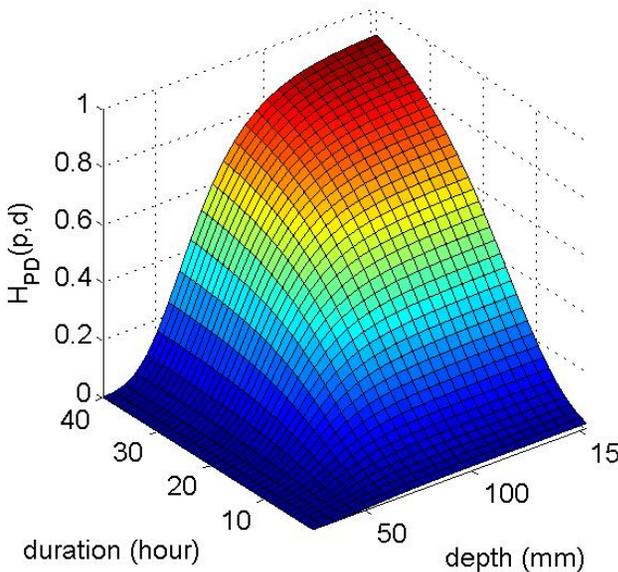
$$H_{PD}(p, d) = C_{UV}(F_P(p), F_D(d)) = C_{UV}(u, v)$$

$$H_{DI}(d, i) = C_{VW}(F_D(d), F_I(i)) = C_{VW}(v, w)$$

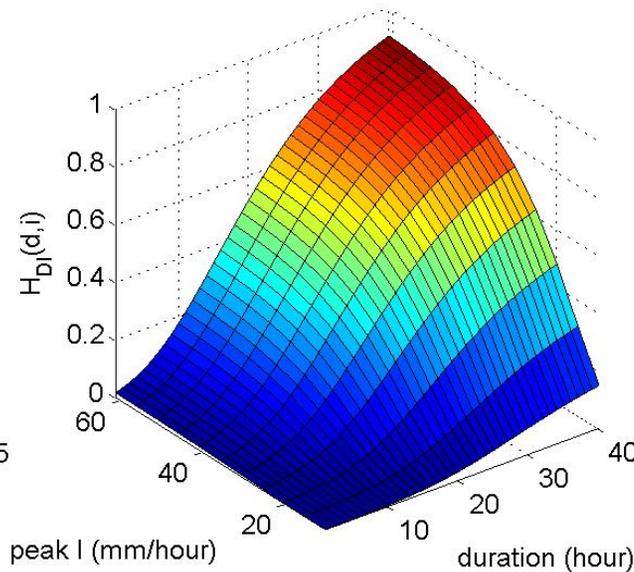
$$H_{PI}(p, i) = C_{UW}(F_P(p), F_I(i)) = C_{UW}(u, w)$$

- Examples using Frank family and EV1 marginals

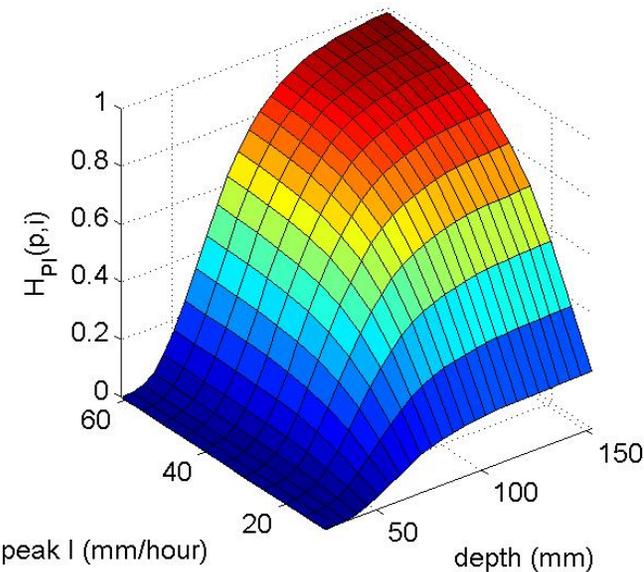
$H_{PD}(p, d)$, AMV events, Station: 120132



$H_{DI}(d, i)$, AMV events, Station: 120132



$H_{PI}(p, i)$, AMV events, Station: 120132



Estimate of depth for known duration (I)



- For a known (or measured) d-hour event

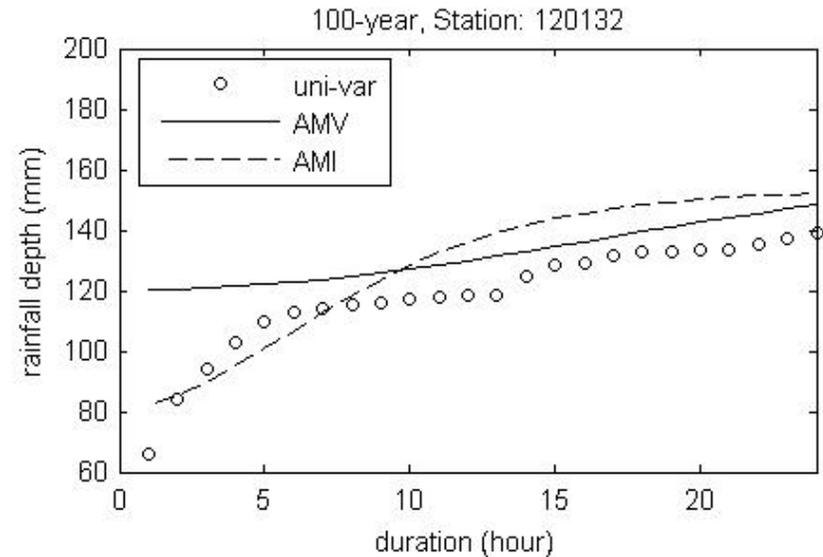
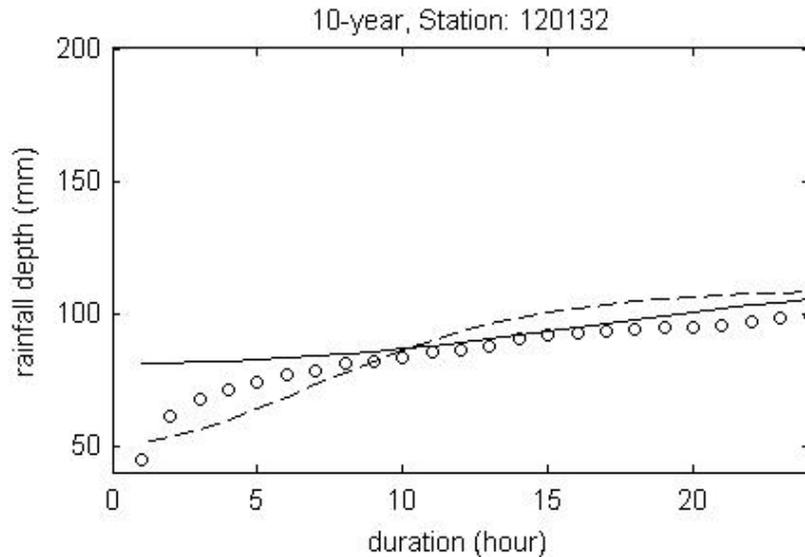
$$\begin{aligned} F_P(p|d-1 < D \leq d) &= \frac{H_{PD}(p, d) - H_{PD}(p, d-1)}{F_D(d) - F_D(d-1)} \\ &= \frac{C_{UV}(F_P(p), F_D(d)) - C_{UV}(F_P(p), F_D(d-1))}{F_D(d) - F_D(d-1)} \end{aligned}$$

- Given return period T, the T-year, d-hour rainfall estimate p_T will satisfy

$$F_P(p_T|d-1 < D \leq d) = 1 - 1/T$$

- Comparison between bivariate and univariate depth estimates
 - Bivariate using EV1 marginals and Frank family
 - Univariate counterpart using GEV distribution (Rao and Kao, 2006)
-

Estimate of depth for known duration (II)



- Similar trends were observed for durations greater than 10-hour, close to the univariate counterpart
- For durations less than 10-hour
 - AMV estimates gave higher values
 - AMI estimates should be better, but fitting problem existed
- Overall, less parameters required for bivariate estimates

Conclusions (I)



- Definition of extreme events
 - AMV events are generally of longer duration than AMI events
 - AMV estimates should be better for longer duration, while AMI estimates being better for shorter duration
 - AMI results could be improved by adopting data with finer temporal resolutions
 - Marginal distributions
 - EV1, GEV, LP3, LN were found to be appropriate marginal models for extreme rainfall
 - GP was found not appropriate for Indiana extreme rainfall data
 - EV1 and LN are recommended
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Conclusions (II)



- Dependence structure
 - Between P and D, positive correlated
 - Between D and I, generally negative correlated
 - Between P and I, positive correlated
 - Frank family is recommended
 - Estimate of depth for known duration
 - Similar results for durations larger than 10 hours
 - AMI estimates should be better for durations less than 10 hours
 - Bivariate approach is more flexible than univariate approach
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**Thank you for listening.
Questions?**
