Package: jointPm (via r-universe)

September 11, 2024

Type Package

Title Risk Estimation Using the Joint Probability Method

Version 2.3.2

Description A bivariate integration method to estimate risk caused by
two extreme and dependent forcing variables.

Depends R (>= 3.0.1)

License GPL (>= 2)

NeedsCompilation no

Encoding UTF-8

BugReports https://github.com/lbelzile/jointPm/issues/

Repository https://lbelzile.r-universe.dev

RemoteUrl https://github.com/lbelzile/jointpm

RemoteRef HEAD

RemoteSha 20d6084bb29a270b38ef58bb3f452f497576efc8

Contents

jointPm-package	*Risk estimation using the joint probability method ('jointPm')*

Description

The overall impact of climate and weather related events such as flooding, wildfires and cyclones is determined by the interaction of many processes acting together. For example, coastal floods may be caused by coincident extreme rainfall and extreme storm tides, floods in confluence regions may depend on simultaneously large flows from two or more tributaries. It is challenging to perform the joint probability analysis of flood risk with multiple forcing variables, because the return period of forcing processes is not directly equivalent to the return period of floods. This package uses a bivariate integration approach to efficiently estimate risk by accounting for two forcing variables at extreme levels.

Author(s)

Feifei Zheng <feifeizheng@zju.edu.cn>, Michael Leonard <michael.leonard@adelaide.edu.au>, Seth Westra <seth.westra@adelaide.edu.au>

References

Zheng, F., S. Westra, and S. A. Sisson (2013), Quantifying the dependence between extreme rainfall and storm surge in the coastal zone, *Journal of Hydrology*, 505(**15**), 172–187, doi:10.1016/j.jhydrol.2013.09.054.

Zheng, F., Westra S. Sisson S. and Leonard M. (2014). Modelling dependence between extreme rainfall and storm surge to estimate coastal flood risk, *Water Resources Research*, 50, pp. 2050–2071, doi:10.1002/2013WR014616

Zheng, F., Leonard M. and Westra S. (2015). Efficient joint probability analysis of flood risk, *Journal of Hydroinformatics*, 17(4), pp. 584–597, doi:10.2166/hydro.2015.052.

Examples

```
library(jointPm)
data(flood)
px = flood$px;
py = flood$py;
z = flood$flood_table;
prm = flood$prm;
pout = flood$pout
binteg(px, py, z, prm, pout,
   model = "log", prob = "ARI",
   nz = 100, ninc = 1000)
```

| binteg | *bivariate integration* |

Description

An efficient approach for bivariate integration.

Usage

```
binteg(px,py,z,prm,pout,model="log",prob="AEP",nz=100,ninc=1000)
```

Arguments

px
: are marginal probabilities (ARIs/AEPs) of X forcing variable associated with rows of z (e.g. rainfall).

py
: are marginal probabilities (ARIs/AEPs) of Y forcing variable associated with columns of z (e.g. storm tides).

z
: is a table of response variable values (e.g., flood levels) for each (x,y) combination.

prm
: is the parameter for the model being used.

pout
: are probabilities (ARIs/AEPs) for which output response variable levels are desired

model
: is the model used, either logistic model ("log", default) or negative logsitic model ("neglog").

prob
: is the manner in which probabilities are specified, either ARI (annual recurrence interval) or annual exceed probability (AEP). See Details

nz
: is the number of response variable contours to be considered across the range of z table.

ninc
: is the number of integration increments for each piecewise section of response variable contour lines.

Details

This package is illustrated for the example of coastal flood levels (the response variable) forced by extreme rainfall (x) and extreme storm tides (y). For this problem, the low bounds of the marginal distributions, i.e. no rainfall (x) and a suitable tide level (such as mean sea level or the lowest astronomical tide) are denoted as ARI=0/AEP=1. "binteg" estimates the flood risk allows for joint dependence between the extreme values of two forcing variables (rainfall and storm tides). Here the logistic and negative logistic model are used to model dependence due to their simplicity and great ability (see Zheng et al. 2014a). The results from "binteg" also include estimates for the cases of complete dependence (alpha=0) and independence (alpha=1) to enable a comparison with the observed dependence strength.

An issue in the use of the proposed integral method is when the response variable table (e.g.flood level table) does not encapsulate the entirety of the boundary function. This can be seen from the

example of this package whenever a flood contour intersects the upper or right-hand bound (as with contours 1.8m and higher that intersect the upper bound of the figure). In order to address this issue, return probabilities of two alternate cases are computed. Taking the h=2 m in (use "plot2" to generate the figure) for illustration, the first case is to project the red contour line (h=2 m) horizontally back to the y axis at the storm tide intersection ARI=500. This caps the largest storm tide at ARI=500, which will result in an overestimate of the return probability. The second case is to extend the red contour line (h=2 m) vertically to infinity, i.e., assuming the largest flood level produced by the storm tides is h=2 m, even if the storm tide ARI tends to infinity . For this case, the return probability is underestimated. Using this approach, the two cases which give over and under estimates are respectively shown different flood levels (see the figure provided by "plot2"). For the given ARIs/AEPs, if the differences of the flood levels from the two cases are insignificant, the provided response variable table is sufficient for estimation. Otherwise a more extended table with larger marginal ARIs/AEPs is required.

Value

Returns a list of results

`p.aep`	are the AEPs that are onsidered
`p.ari`	are the ARIs that are considered
`zout`	are response variable estimates using the observed dependence, complete dependence and independence, see Details
`px`	are given ARIs/AEPs of X variable associated with rows (reproduced from inputs).
`py`	are given ARIs/AEPs of Y variable associated with columns (reproduced from inputs).
`z`	is the given table of response variable values (reproduced from inputs).
`prm`	is the given parameter (reproduced from inputs).
`model`	is the specified model, either logistic model (default) or negative logsitic model (reproduced from inputs).
`prob`	is the specified format of probablity, ARI or AEP (reproduced from inputs).

Author(s)

Feifei Zheng <feifei.zheng@adelaide.edu.au>, Michael Leonard <michael.leonard@adelaide.edu.au>, Seth Westra <seth.westra@adelaide.edu.au>

References

Zheng, F., S. Westra, and S. A. Sisson (2013), Quantifying the dependence between extreme rainfall and storm surge in the coastal zone, Journal of Hydrology, 505(0), 172-187.

Zheng, F., Westra S. Sisson S. and Leonard M. (2014a). Modelling the dependence between extreme rainfall and storm surge to estimate coastal flood risk, Water Resources Research, under review.

Zheng, F., Leonard M. and Westra S. (2014b). An efficient bivariate integration method for joint probability analysis of flood risk, Water Resources Research, under review.

Examples

```
library(jointPm)
data(flood)
px=flood$px;py=flood$py;z=flood$flood_table;prm=flood$prm;pout=flood$pout
binteg(px,py,z,prm,pout,model="log",prob="ARI",nz=100,ninc=1000)
```

---

flood	*Example data of flood levels and dependence strength between extreme rainfall and extreme storm tides from a coastal catchment*

Description

"flood_table" is a matrix of flood levels with 100 different combinations of the rainfall and storm tides in terms of ARIs.
"px" are ARIs of X variable associated with rows (rainfall).
"py" are ARIs of Y variable associated with columns (storm tides).
"pout" are ARIs for which flood levels are estimated with incorporation of joint dependence between extreme rainfall and storm tides.
"prm" is the dependence parameter for the logistic model.

Usage

```
data(flood)
```

Details

For the low bounds of the marginal dsitributions, the lowest astronomical tide and no rainfall are used and ARI=0/AEP=1.

References

Zheng, F., Leonard M. and Westra S. (2014b). An efficient bivariate integration method for joint probability analysis of flood risk, Water Resources Research, under review.

Examples

```
library(jointPm)
data(flood)
```

`Glog`   *Cumulative distribution function of bivariate logistic model*

Description

Glog is cumulative distribution function of bivariate logistic model

Usage

```
Glog(x,y,alpha)
```

Arguments

x   X variable with Frechet scale

y   Y variable with Frechet scale

alpha   dependence parameter between X and Y variables

Details

The bivariate logistic distribution function with parameter alpha is

G(x,y)=exp(-[x^(-1/alpha)+y^(-1/alpha)]^(alpha))

where 0 < alpha <= 1. Complete dependence is obtained in the limit as alpha approaches zero. Independence is obtained when alpha = 1. Note that x and y are assumed to follow the Frechet distribution for easy demonstration, so that G(z)=exp(-1/z), where z=x or y. However, this implies no loss of generality of the characterization of the bivariate extreme value distribution, since any other marginal distributions, whose extremal properties are determined by the univariate characterizations (GEV or GPD), can always be transformed into the standard Frechet form.

Value

Glog gives the distribution function value of x and y specified on a Frechet scale.

References

Coles, S.G. (2001), An introduction to statistical modelling of extreme values, Springer, London.

Gneglog	*Cumulative distribution function of bivariate negative logistic model*

Description

Gneglog is the cumulative distribution function of bivariate negative logistic model

Usage

```
Gneglog(x,y,alpha)
```

Arguments

x   X variable with Frechet scale

y   Y variable with Frechet scale

alpha   dependence parameter between X and Y variables

Details

The bivariate negative logistic distribution function with parameter alpha is

G(x,y)=exp(-1/x-1/y-[x^(1/alpha)+y^(1/alpha)]^(-1/alpha))

where alpha >0. Independence is obtained in the limit as alpha approaches zero. Complete dependence is obtained as alpha tends to infinity Note that x and y follow the Frechet distribution, so that G(z)=exp(-1/z), where z=x or y. However, this implies no loss of generality of the characterization of the bivariate extreme value distribution, since any other marginal distributions, whose extremal properties are determined by the univariate characterizations (GEV or GPD), can always be transformed into the standard Frechet form.

Value

Gneglog gives the distribution function value of x and y specified on a Frechet scale.

References

Coles, S.G. (2001), An introduction to statistical modelling of extreme values, Springer, London.

---

plot1   *shows the bivariate intergration*

Description

This figure shows the contours of the response variable (e.g. flood levels) interpolated from input z and the joint contours of the bivariate density of two forcing variables.

Usage

```
plot1(obj,prob)
```

Arguments

obj   is the output object from the binteg function.

prob   is how the axes show the return probability, either ARI (annual recurrence interval) or annual exceed probability (AEP).

Details

plot1 is the plot overlaying the response variable's contours and the joint probability contours. The exceedance probability for a particular response level is obtained by integrating the joint density for the region above this specified response level. This can be repeated for a range of different response variable levels, and the response variable corresponding to a specific exceedance probability can be found by subsequent interpolation.

References

Zheng, F., S. Westra, and S. A. Sisson (2013), Quantifying the dependence between extreme rainfall and storm surge in the coastal zone, Journal of Hydrology, 505(0), 172-187.

Zheng, F., Leonard M. and Westra S. (2014b). An efficient bivariate integration method for joint probability analysis of flood risk, Water Resources Research, under review.

Examples

```
library(jointPm)
data(flood)
px=flood$px;py=flood$py;z=flood$flood_table;prm=flood$prm;pout=flood$pout
result=binteg(px,py,z,prm,pout,model="log",prob="ARI",nz=100,ninc=1000)
plot1(result,prob="ARI")
```

| plot2 | *a plot showing response variable levels versus return probabilities (ARI/AEP)* |

Description

plot2 shows the univariate response variable levels versus return probabilities (ARI/AEP).

Usage

```
plot2(obj,prob)
```

Arguments

| obj | is the output object from the binteg function. |
| prob | is how the axes show the return probability, either ARI (annual recurrence interval) or annual exceed probability (AEP). |

Details

This figure include response variable levels estimated using the observed dependence, complete dependence (alpha=0) and complete independence (alpha=1) cases.

References

Zheng, F., Leonard M. and Westra S. (2014b). An efficient bivariate integration method for joint probability analysis of flood risk, Water Resources Research, under review.

Examples

```
library(jointPm)
data(flood)
px=flood$px;py=flood$py;z=flood$flood_table;prm=flood$prm;pout=flood$pout
result=binteg(px,py,z,prm,pout,model="log",prob="ARI",nz=100,ninc=1000)
plot2(result,prob="ARI")
```

Index