Package ‘earlywarnings’

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Type Package

Title Early Warning Signals Toolbox for Detecting Critical Transitions in Timeseries

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Description The Early-Warning-Signals Toolbox provides methods for estimating statistical changes in timeseries that can be used for identifying nearby critical transitions. Based on Dakos et al (2012) Methods for Detecting Early Warnings of Critical Transitions in Time Series Illustrated Using Simulated Ecological Data. PLoS ONE 7(7):e41010

Depend R (>+ 2.14.0), lmtest, nortest, stats, som, Kendall,KernSmooth, moments, fields, spam, tseries, quadprog, fractal,akima, ggplot2

LazyLoad yes

URL
`http://www.early-warning-signals.org, http://www.vasilisdakos.net`

Collate 'BDSboot.R' 'bdstest_ews.R' 'ch_ews.R' 'ddjnonparam_ews.R' 'earlywarnings-internal.R' 'generic_ews.R' 'sensitivity_ews.R' 'surrogates_ews.R' 'potential_ews.R'

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`bdstest_ews` *Description: BDS test Early Warning Signals*

Description

`bdstest_ews` is used to estimate the BDS statistic to detect nonlinearity in the residuals of a timeseries after first-difference detrending, fitting an ARMA(p,q) model, and fitting a GARCH(0,1) model. The function is making use of `bds.test`.

Usage

```
bdstest_ews(timeseries, ARMAoptim = TRUE,
  ARMAorder = c(1, 0), GARCHorder = c(0, 1), embdim = 3,
  epsilon = c(0.5, 0.75, 1), boots = 1000,
  logtransform = FALSE, interpolate = FALSE)
```

Arguments

`timeseries`	a numeric vector of the observed univariate timeseries values or a numeric matrix where the first column represents the time index and the second the observed timeseries values. Use vectors/matrices with headings.
`ARMAoptim`	is the order of the `ARMA(p,q)` model to be fitted on the original timeseries. If TRUE the best ARMA model based on AIC is applied. If FALSE the `ARMAorder` is used.
`ARMAorder`	is the order of the `AR(p)` and `MA(q)` process to be fitted on the original timeseries. Default is `p=1 q=0`.
`GARCHorder`	fits a GARCH model on the original timeseries where `GARCHorder[1]` is the GARCH part and `GARCHorder[2]` is the ARCH part.
`embdim`	is the embedding dimension (2, 3,... `embdim`) up to which the BDS test will be estimated (must be numeric). Default value is 3.
`epsilon`	is a numeric vector that is used to scale the standard deviation of the timeseries. The BDS test is computed for each element of epsilon. Default is 0.5, 0.75 and 1.
`boots`	is the number of bootstraps performed to estimate significance p values for the BDS test. Default is 1000.
`logtransform`	logical. If TRUE data are logtransformed prior to analysis as log(X+1). Default is FALSE.
`interpolate`	logical. If TRUE linear interpolation is applied to produce a timeseries of equal length as the original. Default is FALSE (assumes there are no gaps in the timeseries).

Details

See also `bds.test{tseries}` for more details. The function requires the installation of packages `tseries` and `quadprog` that are not available under Linux and need to be manually installed under Windows.

Example to run after installing the mentioned packages:

data(foldbif) bdstest_ews(foldbif,ARMAoptim=FALSE,ARMAorder=c(1,0),embdim=3,epsilon=0.5, boots=200,logtransform=FALSE,interpolate=FALSE)

Value

`bdstest_ews` returns output on the R console that summarizes the BDS test statistic for all embedding dimensions and `epsilon` values used, and for first-differenced data, ARMA(p.q) residuals, and GARCH(0,1) residuals). Also the significance p values are returned estimated both by comparing to a standard normal distribution and by bootstrapping.

In addition, `bdstest_ews` returns a plot with the original timeseries, the residuals after first-differencing, and fitting the ARMA(p,q) and GARCH(0,1) models. Also the autocorrelation `acf` and partial autocorrelation `pacf` functions are estimated serving as guides for the choice of lags of the linear models fitted to the data.

Author(s)

S. R. Carpenter, modified by V. Dakos

References

J. B. Cromwell, W. C. Labys and M. Terraza (1994): Univariate Tests for Time Series Models, Sage, Thousand Oaks, CA, pages 32-36.

Dakos, V., et al (2012)."Methods for Detecting Early Warnings of Critical Transitions in Time Series Illustrated Using Simulated Ecological Data." *PLoS ONE* 7(7): e41010. doi:10.1371/journal.pone.0041010

See Also

`generic_ews`; `ddjnonparam_ews`; `bdstest_ews`; `sensitivity_ews`; `surrogates_ews`; `ch_ews`; `movpotential_ews`; `livpotential_ews`

`ch_ews` *Description: Conditional Heteroskedasticity*

Description

`ch_ews` is used to estimate changes in conditional heteroskedasticity within rolling windows along a timeseries

Usage

```
ch_ews(timeseries, winsize = 10, alpha = 0.1,
  optim = TRUE, lags = 4, logtransform = FALSE,
  interpolate = FALSE)
```

Arguments

- `timeseries` a numeric vector of the observed timeseries values or a numeric matrix where the first column represents the time index and the second the observed timeseries values. Use vectors/matrices with headings.
- `winsize` is length of the rolling window expressed as percentage of the timeseries length (must be numeric between 0 and 100). Default is 10%.
- `alpha` is the significance threshold (must be numeric). Default is 0.1.
- `optim` logical. If TRUE an autoregressive model is fit to the data within the rolling window using AIC optimization. Otherwise an autoregressive model of specific order `lags` is selected.
- `lags` is a parameter that determines the specific order of an autoregressive model to fit the data. Default is 4.
- `logtransform` logical. If TRUE data are logtransformed prior to analysis as log(X+1). Default is FALSE.
- `interpolate` logical. If TRUE linear interpolation is applied to produce a timeseries of equal length as the original. Default is FALSE (assumes there are no gaps in the timeseries).

Details

see ref below

Value

`ch_ews` returns a matrix that contains:

- `time` the time index.
- `r.squared` the R2 values of the regressed residuals.
- `critical.value` the chi-square critical value based on the desired `alpha` level for 1 degree of freedom divided by the number of residuals used in the regression.
- `test.result` logical. It indicates whether conditional heteroskedasticity was significant.
- `ar.fit.order` the order of the specified autoregressive model- only informative if `optim` FALSE was selected.

In addition, `ch_ews` plots the original timeseries and the R2 where the level of significance is also indicated.

Author(s)

T. Cline, modified by V. Dakos

References

Seekell, D. A., et al (2011). "Conditional heteroscedasticity as a leading indicator of ecological regime shifts." *American Naturalist* 178(4): 442-451

Dakos, V., et al (2012)."Methods for Detecting Early Warnings of Critical Transitions in Time Series Illustrated Using Simulated Ecological Data." *PLoS ONE* 7(7): e41010. doi:10.1371/journal.pone.0041010

See Also

`generic_ews`; `ddjnonparam_ews`; `bdstest_ews`; `sensitivity_ews`; `surrogates_ews`; `ch_ews`; `movpotential_ews`; `livpotential_ews`

Examples

```
data(foldbif)
out=ch_ews(foldbif, winsize=50, alpha=0.05, optim=TRUE, lags)
```

`circulation` *Overturning of thermolhaline circulation*

Description

Simulated timeseries of salinity from an ocean circulation model

Usage

```
data(circulation)
```

Format

A data frame with 783 observations on the following 2 variables.

`time` a numeric vector

`x` a numeric vector

Details

Simulated timeseries of salinity from an ocean circulation model as used in Dakos et al (2008), see source below. At the end of the timeseries a critical transition occurs that simulates the overturning of the thermohalien circulation.

Source

Dakos et al (2008), Slowing down as an early warning signal for abrup climate change, PNAS 105(38), 14308-14312.

ddjnonparam_ews *Description: Drift Diffusion Jump Nonparametrics Early Warning Signals*

Description

ddjnonparam_ews is used to compute nonparametrically conditional variance, drift, diffusion and jump intensity in a timeseries. It also interpolates to obtain the evolution of the nonparametric statistics in time.

Usage

```
ddjnonparam_ews(timeseries, bandwidth = 0.6, na = 500,
  logtransform = TRUE, interpolate = FALSE)
```

Arguments

timeseries	a numeric vector of the observed univariate timeseries values or a numeric matrix where the first column represents the time index and the second the observed timeseries values. Use vectors/matrices with headings.
bandwidth	is the bandwidht of the kernel regressor (must be numeric). Default is 0.6.
na	is the number of points for computing the kernel (must be numeric). Default is 500.
logtransform	logical. If TRUE data are logtransformed prior to analysis as log(X+1). Default is FALSE.
interpolate	logical. If TRUE linear interpolation is applied to produce a timeseries of equal length as the original. Default is FALSE (assumes there are no gaps in the timeseries).

Details

The approach is based on estimating terms of a drift-diffusion-jump model as a surrogate for the unknown true data generating process: [1] $dx = f(x,\theta)dt + g(x,\theta)dW + dJ$ Here x is the state variable, f() and g() are nonlinear functions, dW is a Wiener process and dJ is a jump process. Jumps are large, one-step, positive or negative shocks that are uncorrelated in time.

Value

ddjnonparam_ews returns an object with elements:

avec	is the mesh for which values of the nonparametric statistics are estimated.
S2.vec	is the conditional variance of the timeseries x over avec.
TotVar.dx.vec	is the total variance of dx over avec.
Diff2.vec	is the diffusion estimated as total variance - jumping intensity vs avec.
LamdaZ.vec	is the jump intensity over avec.
Tvec1	is the timeindex.
S2.t	is the conditional variance of the timeseries x data over Tvec1.

`TotVar.t`	is the total variance of `dx` over `Tvec1`.
`Diff2.t`	is the diffusion over `Tvec1`.
`Lamda.t`	is the jump intensity over `Tvec1`.

In addition, `ddjnonparam_ews` returns a first plot with the original timeseries and the residuals after first-differencing. A second plot shows the nonparametric conditional variance, total variance, diffusion and jump intensity over the data, and a third plot the same nonparametric statistics over time.

Author(s)

S. R. Carpenter, modified by V. Dakos

References

Carpenter, S. R. and W. A. Brock (2011). "Early warnings of unknown nonlinear shifts: a nonparametric approach." *Ecology* 92(12): 2196-2201

Dakos, V., et al (2012)."Methods for Detecting Early Warnings of Critical Transitions in Time Series Illustrated Using Simulated Ecological Data." *PLoS ONE* 7(7): e41010. doi:10.1371/journal.pone.0041010

See Also

`generic_ews`; `ddjnonparam_ews`; `bdstest_ews`; `sensitivity_ews`;`surrogates_ews`; `ch_ews`; `movpotential_ews`; `livpotential_ews`

Examples

```
data(foldbif)
output<-ddjnonparam_ews(foldbif,bandwidth=0.6,na=500,
logtransform=TRUE,interpolate=FALSE)
```

`foldbif` *Simulated fold bifurcation time series*

Description

Simulated time series of a transition to an alternative state.

Usage

```
data(foldbif)
```

Format

A data frame with 970 observations on the following variable.

`x` a numeric vector

Details

Simulated time series of a transition to an alternative state derived from a simple overharvesting model as used in Dakos et al (2012), see source below.

Source

Dakos et al (2012) Methods for Detecting Early Warnings of Critical Transitions in Time Series Illustrated Using Simulated Ecological Data. PLoS ONE 7(7):e41010

`generic_ews` *Description: Generic Early Warning Signals*

Description

`generic_ews` is used to estimate statistical moments within rolling windows along a timeserie

Usage

```
generic_ews(timeseries, winsize = 50,
  detrending = c("no", "gaussian", "linear", "first-diff"),
  bandwidth = NULL, logtransform = FALSE,
  interpolate = FALSE, AR_n = FALSE,
  powerspectrum = FALSE)
```

Arguments

`timeseries`	a numeric vector of the observed univariate timeseries values or a numeric matrix where the first column represents the time index and the second the observed timeseries values. Use vectors/matrices with headings. If the powerspectrum is to be plotted as well, the timeseries lenght should be even number.
`winsize`	is the size of the rolling window expressed as percentage of the timeseries length (must be numeric between 0 and 100). Default is 50%.
`bandwidth`	is the bandwidth used for the Gaussian kernel when gaussian filtering is applied. It is expressed as percentage of the timeseries length (must be numeric between 0 and 100). Alternatively it can be given by the bandwidth selector `bw.nrd0` (Default).
`detrending`	the timeseries can be detrended/filtered prior to analysis. There are four options: `gaussian` filtering, `linear` detrending and `first-differencing`. Default is `no` detrending.
`logtransform`	logical. If TRUE data are logtransformed prior to analysis as log(X+1). Default is FALSE.
`interpolate`	logical. If TRUE linear interpolation is applied to produce a timeseries of equal length as the original. Default is FALSE (assumes there are no gaps in the timeseries).
`AR_n`	logical. If TRUE the best fitted AR(n) model is fitted to the data. Default is FALSE.
`powerspectrum`	logical. If TRUE the power spectrum within each rolling window is plotted. Default is FALSE.

Details

see ref below

Value

generic_ews returns a matrix that contains:

tim	the time index.
ar1	the autoregressive coefficient ar(1) of a first order AR model fitted on the data within the rolling window.
sd	the standard deviation of the data estimated within each rolling window.
sk	the skewness of the data estimated within each rolling window.
kurt	the kurtosis of the data estimated within each rolling window.
cv	the coefficient of variation of the data estimated within each rolling window.
returnrate	the return rate of the data estimated as 1-ar(1) cofficient within each rolling window.
densratio	the density ratio of the power spectrum of the data estimated as the ratio of low frequencies over high frequencies within each rolling window.
acf1	the autocorrelation at first lag of the data estimated within each rolling window.

In addition, generic_ews returns three plots. The first plot contains the original data, the detrending/filtering applied and the residuals (if selected), and all the moment statistics. For each statistic trends are estimated by the nonparametric Kendall tau correlation. The second plot, if asked, quantifies resilience indicators fitting AR(n) selected by the Akaike Information Criterion. The third plot, if asked, is the power spectrum estimated by spec.ar for all frequencies within each rolling window.

Author(s)

Vasilis Dakos <vasilis.dakos@gmail.com>

References

Ives, A. R. (1995). "Measuring resilience in stochastic systems." *Ecological Monographs* 65: 217-233

Dakos, V., et al (2008). "Slowing down as an early warning signal for abrupt climate change." *Proceedings of the National Academy of Sciences* 105(38): 14308-14312

Dakos, V., et al (2012)."Methods for Detecting Early Warnings of Critical Transitions in Time Series Illustrated Using Simulated Ecological Data." *PLoS ONE* 7(7): e41010. doi:10.1371/journal.pone.0041010

See Also

generic_ews; ddjnonparam_ews; bdstest_ews; sensitivity_ews; surrogates_ews; ch_ews; movpotential_ews; livpotential_ews

Examples

```
data(foldbif)
 out=generic_ews(foldbif,winsize=50,detrending="gaussian",
 bandwidth=5,logtransform=FALSE,interpolate=FALSE)
```

livpotential_ews *Description: Potential Analysis*

Description

livpotential_ews performs one-dimensional potential estimation derived from a uni-variate timeseries

Usage

```
livpotential_ews(x, std = 1, bw = -1, xi = NULL,
  weights = c(), grid.size = 200)
```

Arguments

x	data vector
std	the standard deviation of the noise (defaults to 1, so then you use scaled potentials
bw	bandwidth for kernel estimation
xi	x values at which the potential is estimated
weights	optional weights in ksdensity (used by movpotentials).
grid.size	grid size

Details

see ref below

Value

livpotential returns a list with the following elements:

xi	the grid of points on which the potential is estimated
pot	the actual value of the potential
minima	the grid points at which the potential has minimum values
maxima	the grid points at which the potential has maximum values
bw	bandwidth of kernel used

Author(s)

Based on Matlab code from Egbert van Nes modified by Leo Lahti. Implemented in early warnings package by V. Dakos.

References

Livina, VN, F Kwasniok, and TM Lenton, 2010. Potential analysis reveals changing number of climate states during the last 60 kyr . *Climate of the Past*, 6, 77-82.

Dakos, V., et al (2012)."Methods for Detecting Early Warnings of Critical Transitions in Time Series Illustrated Using Simulated Ecological Data." *PLoS ONE* 7(7): e41010. doi:10.1371/journal.pone.0041010

See Also

`generic_ews`; `ddjnonparam_ews`; `bdstest_ews`; `sensitivity_ews`;`surrogates_ews`; `ch_ews`;`movpotential_ews`

Examples

```
data(foldbif)
res <- livpotential_ews(foldbif)
plot(res$xi, res$pot)
```

`movpotential_ews` *Description: Moving Average Potential*

Description

`movpotential_ews` reconstructs a potential derived from data along a gradient of a given parameter the `movpotential_ews` calculates the potential for values that correspond to a particular parameter. see ref below

Usage

```
movpotential_ews(X, param, sdwindow = NULL, bw = -1,
  minparam = NULL, maxparam = NULL, npoints = 50,
  thres = 0.002, std = 1, grid.size = 200, cutoff = 0.5)
```

Arguments

`X`	a vector of the X observations of the state variable of interest
`param`	parameter values that correspond to the X observations
`sdwindow`	window for smoothing kernels (over the `param` axis)
`bw`	bandwidth used for smoothing kernels
`minparam`	minimum value of parameter on which to estimate potential
`maxparam`	maximum value of parameter on which to estimate potential
`npoints`	number of potentials
`thres`	threshold for local minima to be discarded
`std`	std
`grid.size`	number of evaluation points
`cutoff`	the cuttof value to estimate minima and maxima in the potential Returns:

Value

A list with the following elements:

`pars`	values of the covariate parameter as matrix
`xis`	values of the x as matrix
`pots`	smoothed potentials
`mins`	minima in the densities (-potentials; neglecting local optima)
`maxs`	maxima in densities (-potentials; neglecting local optima)
`plot`	an object that displays the potential estimated in 2D

Author(s)

Based on Matlab code from Egbert van Nes modified by Leo Lahti. Implemented in early warnings package by V. Dakos.

References

Hirota, M., Holmgren, M., van Nes, E.H. & Scheffer, M. (2011). Global resilience of tropical forest and savanna to critical transitions. *Science*, 334, 232-235.

See Also

`generic_ews`; `ddjnonparam_ews`; `bdstest_ews`; `sensitivity_ews`;`surrogates_ews`; `ch_ews`; `livpotential_ews`

Examples

```
X = c(rnorm(1000, mean = 0), rnorm(1000, mean = -2), rnorm(1000, mean = 2))
 param = seq(0,5,length=3000)
 res <- movpotential_ews(X, param, npoints = 100, thres = 0.003)
```

---

sensitivity_ews *Description: Sensitivity Early Warning Signals*

Description

`sensitivity_ews` is used to estimate trends in statistical moments for different sizes of rolling windows along a timeseries. The trends are estimated by the nonparametric Kendall tau correlation coefficient.

Usage

```
sensitivity_ews(timeseries,
  indicator = c("ar1", "sd", "acf1", "sk", "kurt", "cv", "returnrate", "densra
  winsizerange = c(25, 75), incrwinsize = 25,
  detrending = c("no", "gaussian", "linear", "first-diff"),
  bandwidthrange = c(5, 100), incrbandwidth = 20,
  logtransform = FALSE, interpolate = FALSE)
```

Arguments

`timeseries` a numeric vector of the observed univariate timeseries values or a numeric matrix where the first column represents the time index and the second the observed timeseries values. Use vectors/matrices with headings.

`indicator` is the statistic (leading indicator) selected for which the sensitivity analysis is perfomed. Currently, the indicators supported are: `ar1` autoregressive coefficient of a first order AR model, `sd` standard deviation, `acf1` autocorrelation at first lag, `sk` skewness, `kurt` kurtosis, `cv` coeffcient of variation, `returnrate`, and `densratio` density ratio of the power spectrum at low frequencies over high frequencies.

`winsizerange` is the range of the rolling window sizes expressed as percentage of the timeseries length (must be numeric between 0 and 100). Default is 25% - 75%.

`incrwinsize` increments the rolling window size (must be numeric between 0 and 100). Default is 25.

`detrending` the timeseries can be detrended/filtered. There are three options: `gaussian` filtering, `linear` detrending and `first-differencing`. Default is `no` detrending.

`bandwidthrange` is the range of the bandwidth used for the Gaussian kernel when gaussian filtering is selected. It is expressed as percentage of the timeseries length (must be numeric between 0 and 100). Default is 5% - 100%.

`incrbandwidth` is the size to increment the bandwidth used for the Gaussian kernel when gaussian filtering is applied. It is expressed as percentage of the timeseries length (must be numeric between 0 and 100). Default is 20.

`logtransform` logical. If TRUE data are logtransformed prior to analysis as log(X+1). Default is FALSE.

`interpolate` logical. If TRUE linear interpolation is applied to produce a timeseries of equal length as the original. Default is FALSE (assumes there are no gaps in the timeseries).

Details

see ref below

Value

`sensitivity_ews` returns a matrix that contains the Kendall tau rank correlation estimates for the rolling window sizes (rows) and bandwidths (columns), if `gaussian filtering` is selected.

In addition, `sensitivity_ews` returns a plot with the Kendall tau estimates and their p-values for the range of rolling window sizes used, together with a histogram of the distributions of the statistic and its significance. When `gaussian filtering` is chosen, a contour plot is produced for the Kendall tau estimates and their p-values for the range of both rolling window sizes and bandwidth used. A reverse triangle indicates the combination of the two parameters for which the Kendall tau was the highest

Author(s)

Vasilis Dakos `<vasilis.dakos@gmail.com>`

References

Dakos, V., et al (2008). "Slowing down as an early warning signal for abrupt climate change." *Proceedings of the National Academy of Sciences* 105(38): 14308-14312

Dakos, V., et al (2012)."Methods for Detecting Early Warnings of Critical Transitions in Time Series Illustrated Using Simulated Ecological Data." *PLoS ONE* 7(7): e41010. doi:10.1371/journal.pone.0041010

See Also

`generic_ews`; `ddjnonparam_ews`; `bdstest_ews`; `sensitivity_ews`; `surrogates_ews`; `ch_ews`; `movpotential_ews`; `livpotential_ews`

Examples

```
data(foldbif)
output=sensitivity_ews(foldbif,indicator="sd",detrending="gaussian",
incrwinsize=25,incrbandwidth=20)
```

---

surrogates_ews *Description: Surrogates Early Warning Signals*

Description

`surrogates_ews` is used to estimate distributions of trends in statistical moments from different surrogate timeseries generated after fitting an ARMA(p,q) model on the data. The trends are estimated by the nonparametric Kendall tau correlation coefficient and can be compared to the trends estimated in the original timeseries to produce probabilities of false positives.

Usage

```
surrogates_ews(timeseries,
  indicator = c("ar1", "sd", "acf1", "sk", "kurt", "cv", "returnrate", "densra
  winsize = 50,
  detrending = c("no", "gaussian", "linear", "first-diff"),
  bandwidth = NULL, boots = 100, logtransform = FALSE,
  interpolate = FALSE)
```

Arguments

`timeseries`	a numeric vector of the observed univariate timeseries values or a numeric matrix where the first column represents the time index and the second the observed timeseries values. Use vectors/matrices with headings.
`indicator`	is the statistic (leading indicator) selected for which the surrogate timeseries are produced. Currently, the indicators supported are: `ar1` autoregressive coefficient of a first order AR model, `sd` standard deviation, `acf1` autocorrelation at first lag, `sk` skewness, `kurt` kurtosis, `cv` coeffcient of variation, `returnrate`, and `densratio` density ratio of the power spectrum at low frequencies over high frequencies.
`winsize`	is the size of the rolling window expressed as percentage of the timeseries length (must be numeric between 0 and 100). Default valuise 50%.
`detrending`	the timeseries can be detrended/filtered prior to analysis. There are three options: `gaussian` filtering, `linear` detrending and `first-diff`erencing. Default is `no` detrending.
`bandwidth`	is the bandwidth used for the Gaussian kernel when gaussian filtering is selected. It is expressed as percentage of the timeseries length (must be numeric between 0 and 100). Alternatively it can be given by the bandwidth selector `bw.nrd0` (Default).
`boots`	the number of surrogate data. Default is 100.
`logtransform`	logical. If TRUE data are logtransformed prior to analysis as log(X+1). Default is FALSE.
`interpolate`	logical. If TRUE linear interpolation is applied to produce a timeseries of equal length as the original. Default is FALSE (assumes there are no gaps in the timeseries).

Details

see ref below

Value

surrogates_ews returns a matrix that contains:

Kendall tau estimate original
: the trends of the original timeseries.

Kendall tau p-value original
: the p-values of the trends of the original timeseries.

Kendall tau estimate surrogates
: the trends of the surrogate timeseries.

Kendall tau p-value surrogates
: the associated p-values of the trends of the surrogate timeseries.

significance p
: the p-value for the original Kendall tau rank correlation estimate compared to the surrogates.

In addition, surrogates_ews returns a plot with the distribution of the surrogate Kendall tau estimates and the Kendall tau estimate of the original series. Vertical lines indicate the 5% and 95% significance levels.

Author(s)

Vasilis Dakos <vasilis.dakos@gmail.com>

References

Dakos, V., et al (2008). "Slowing down as an early warning signal for abrupt climate change." *Proceedings of the National Academy of Sciences* 105(38): 14308-14312

Dakos, V., et al (2012)."Methods for Detecting Early Warnings of Critical Transitions in Time Series Illustrated Using Simulated Ecological Data." *PLoS ONE* 7(7): e41010. doi:10.1371/journal.pone.0041010

See Also

generic_ews; ddjnonparam_ews; bdstest_ews; sensitivity_ews; surrogates_ews; ch_ews; movpotential_ews; livpotential_ews

Examples

```
data(foldbif);
output=surrogates_ews(foldbif,indicator="sd",winsize=50,detrending="gaussian",
bandwidth=10,boots=200,logtransform=FALSE,interpolate=FALSE)
```

YD2PB_grayscale *Younger Dryas to PreBoreal transition*

Description

Grayscale paleodata of the exit from the Younger Dryas

Usage

```
data(YD2PB_grayscale)
```

Format

A data frame with 2111 observations on the following 2 variables.

`time` a numeric vector

`x` a numeric vector

Details

Grayscale paleodata as proxy of exit from Younger Dryas as used in Dakos et al (2008), see source below.

Source

Dakos et al (2008), Slowing down as an early warning signal for abrup climate change, PNAS 105(38), 14308-14312.