

European Windstorm Event Response Service

From real time forecasts to historical analogues Bernd Becker, Met Office, 1st September 2015



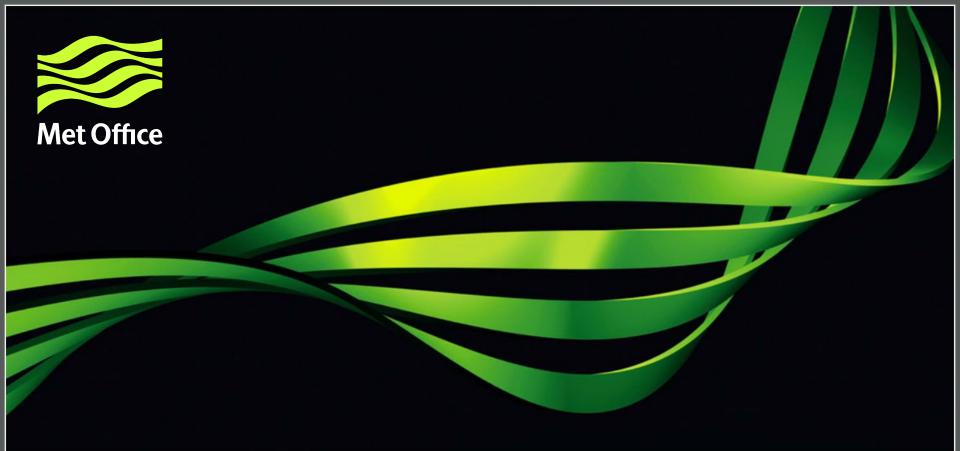
Collaborators

Applied climate science Insurance and Capital Markets team: Paul Maisey, Claire Scannell, Hamish Steptoe, Lorna Mitchell Building on the Unified Model MOGREPS ensemble 7-day forecast (33km) European 5-day forecast Historical Windstorm Catalogue At 4 km resolution



Contents

Introduction Real time storm footprints Ensemble heads-up Deterministic forecasts Real time analysis (Return periods) Matching historical storms Clusters Real time guidance in damage terms: a concept



Introduction

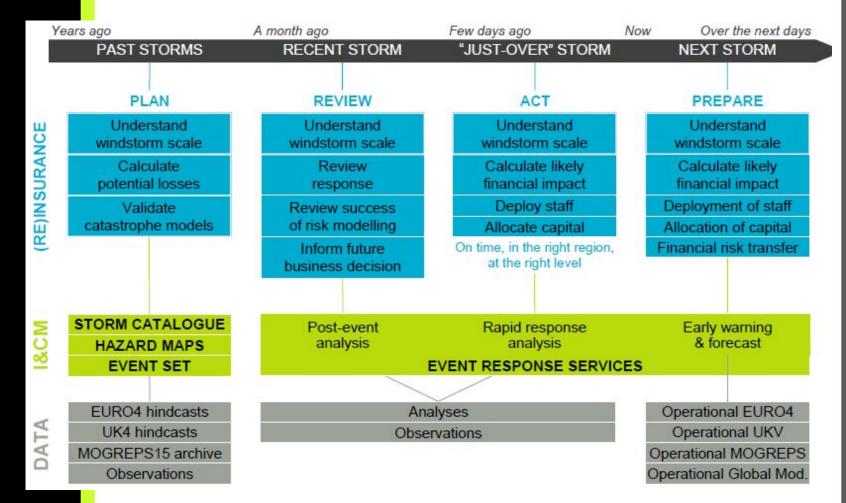
What do we do?

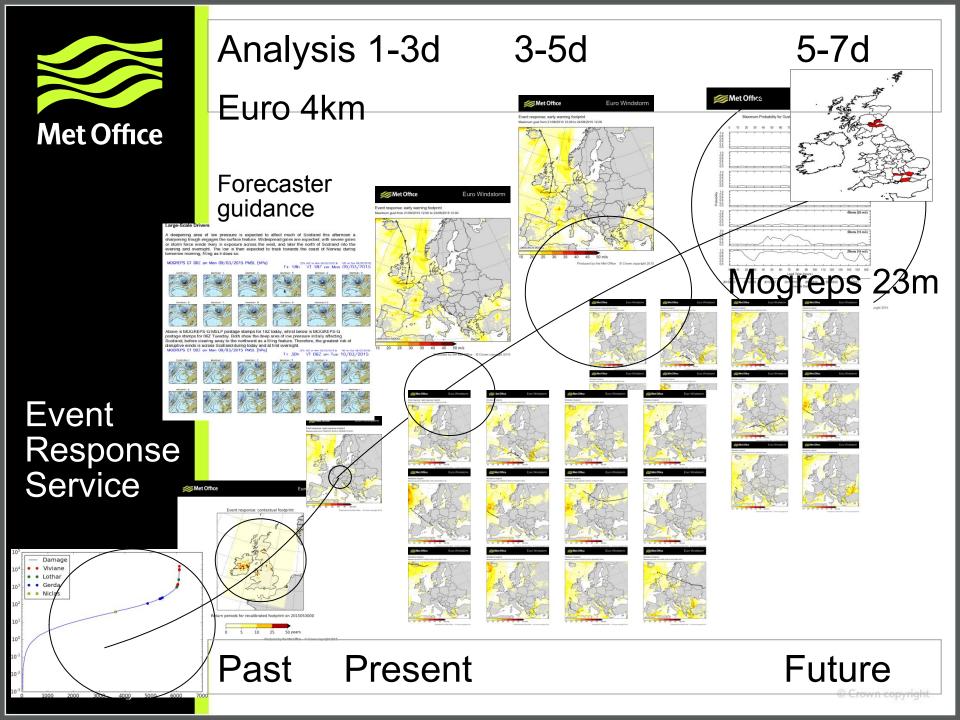
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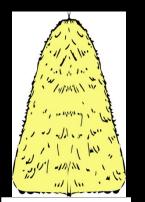


Products & Activities





Met Office



Haystack

Historical Windstorm Catalogue (72 hours at 4 km)

Commercially available

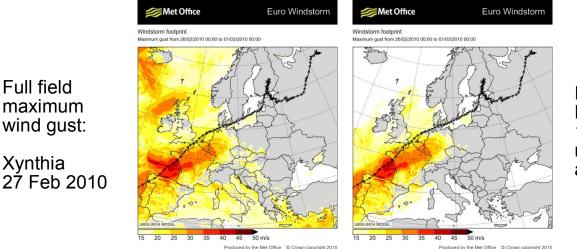
Full field

maximum

wind gust:

Xynthia

- for both commercial and academic use Contains information on storm tracks, surface winds and windstorm footprints for storms over the past 35 years (6110 storms) Facilitates research into storm characteristics and the influence of large-scale atmospheric variability on European windstorms Provides a common performance benchmark for both catastrophe models and climate models



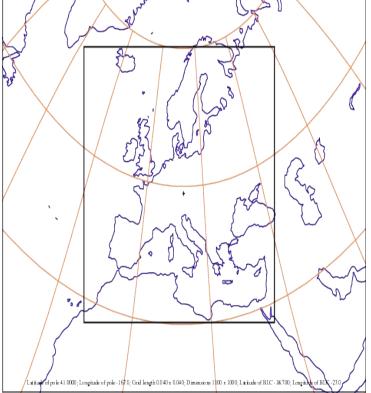
Foot print: Decontaminated 1000 km radius around track



The real time forecast system

- State of the art, world leading, operational, high resolution
- EURO4: European 4.4km Global down-scaling model enlarged domain to cover most of Europe driven by 3-hourly

Global boundary conditions starting from the Global T+0 analysis.





The operational storm footprint (SFP) monitor

Post-processing the latest EURO4 run every 6 hours

Concatenate short range forecast period t+3 to t+9 from consecutive forecasts to describe a 72 hour time series in the recent past

Event Response Rapid Response: past 72 hours Complement with:

Event Response Early Warning: 1-3-5 day forecast



The operational storm footprint (SFP) monitor provides:

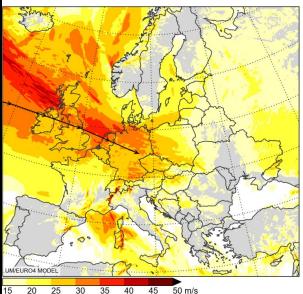
Euro Windstorm

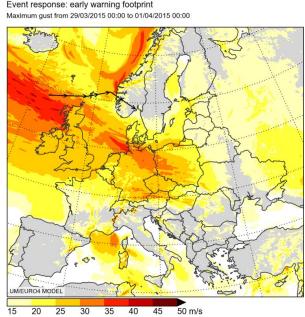
<mark>E</mark>arly Warning



Euro Windstorm

Event response: rapid response footprint Maximum gust from 29/03/2015 00:00 to 01/04/2015 00:00





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Rapid response

A succinct description of the latest SFP close to real time.

May provide near real time forcing data for CAT models.

May be extended into longer lead times

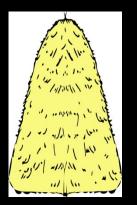
(images, gridded data, geotiffs, csv) (Niklas)

Needle

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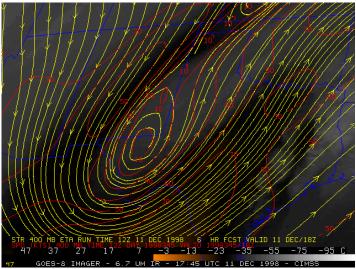
"Matching" challenge

To put current extreme wind events into perspective: Find real time storm footprint (SFP) data (the needle) In a catalogue of past events (in the haystack) Provide re/insurers with historical wind storm data similar to the current/most recent event Known impacts of historical storms in (user) terms of damage, claims, loss, costs Guide customers during the planning stages in mitigating the impact of the most recent event. May provide forcing data for CATastrophe models



Idea: compare fingerprint and streamlines





Fingerprint reading software now commonplace, on every phone.

What software is available for computer vision and image processing, searching for similarities and feature tracking?



Matching storm footprints: blind alleys...

/net/data/cr1/jroberts/XWS/all_footprints_3deg_dates/fp_4501_*.pp target foot print no: fp 10 1979101700.pp foot print no: fp 10 1979101700.pp 2005-03-31 00:00:00 No.:4501 Histonram of a www.metoffice.gov.uk

Using a single feature to describe a SFP:

- mean variance (longitude) * mean variance (latitude)
- Draw one histogram from a north-south oriented strip of data and another from an east-west oriented strip of data. Calculate Wilcoxon rank sum statistic to describe the departure from "blobbiness" (here we are dipping our toe into feature analysis!)

Insufficient discrimination: similar numbers describe dissimilar SFP

Try computer vision for indexing database of SFP



Haralick texture features:

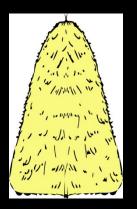


- Derived from the Gray-Level-Co-occurrence matrix
- Defined over an image, to be the distribution of co-occurring values at a given offset which
- Contains information about how image intensities in pixels with a certain position in relation to each other occur together.
- Mahotas computer image processing library for Python calculates thirteen features for each SFP

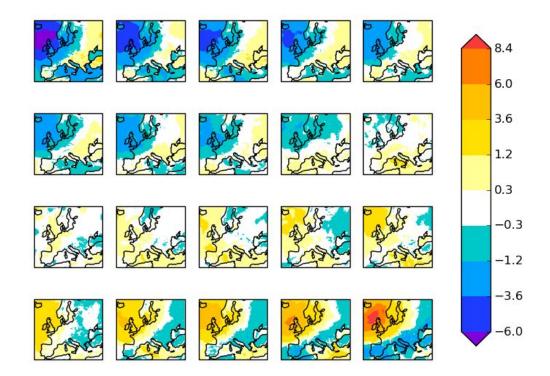
- H1: Angular Second Moment
- H2: Contrast
- H3: Correlation
- H4: Sum of Squares: Variation
- H5: Inverse Difference Moment
- H6: Sum Average
- H7: Sum Variance
- H8: Sum Entropy
- H9: Entropy
- H10: Difference Variance
- H11: Difference Entropy
- H12: Information Measure of Correlation 1
- H13: Information Measure of Correlation 2

Robert M Haralick, K Shanmugam, Its'hak Dinstein (1973). "Textural Features for Image Classification". IEEE Transactions on Systems, Man, and Cybernetics. SMC-3 (6): 610–621.





Sufficient discrimination



Ranked mean Haralick image texture features for each of the 6110 storm foot prints:

Plotted averages of 20 chunks at 305 storms blurs the characteristics of individual events but the overall change in the pattern is promising

Sign of the potential of the method to finding similar features between recently observed and historically reported European windstorms. (or helps us to find the needle in the haystack)



Match decision tree, machine learning

Learn closest similarity by ranking a list of similarity measures and by choice of closest members.

For each storm footprint (SFP), save:

SFP number Date

Longitude (average from U > 25 m/s mask)

Latitude (average from U > 25 m/s mask)

Storm intensity over SFP area (3)

13 Haralick features (*4)

Expandable to many more storm features!

Add current storm to catalogue and find best possible match (twin) Note nearest neighbours (rank retrieval mode)

Keep a number of similar candidates to evaluate and plot

Calculate (costly!) distance measures to confirm closest candidate



Evaluation of close matches

In each similarity measure of Storm footprints (SFP) we:

- Note the distance in rank for each measure
- Pick the top N best matches
- Calculate the distance ||F|| between candidate and group members
- Pick a winner
- 1. Rank proximity measure:

Count positional distance in rank from perfect match in each category, integrate over all categories and declare the winner with the smallest rank proximity measure



Best Match RPM : 1751, 427, 86, 2586, 404, 1954, 4203, 2777, 5105, 3174, 6 8 13 14 15 21 24 24 25 27

Feature: 1:			2:		3:		4:	1954	5:	
2586 86 404 1954 1751 Candi 4203 427 3174 5105 2777	-5 -4 -3 -2 -1 0 1 2 3 4 5	2777 3174 5105 1954 4203 1751 1634 404 2586 427 86	-5 -4 -3 -2 -1 0 1 2 3 4 5	1751 86 1634 427 2586 404 1954 4203 3174 5105 2777	-5 -4 -3 -2 -1 0 1 2 3 4 5	86 427 1634 1751 2586 404 2777 1954 5105 3174 4203	-5 -4 -3 -2 -1 0 1 2 3 4 5	3174 404 5105 2586 2777 1751 1634 427 86	-5 -4 -3 -2 -1 0 1 2 3 4 5	

No. 1634 Best match **F**: 1751, 427, 86, 2586, 2777, 3174, 404, 5105, 4203, 1954.



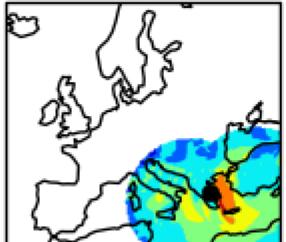
Match for Candidate 1634 is 1751!

The storm from 5 October 1989 in the Aegean Sea (Diagnostics of Cyclogenesis Over the Aegean Sea Using Potential Vorticity Inversion, H. A. Flocas) is very similar to

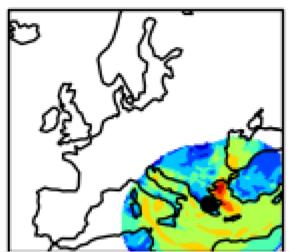
The storm on December 16th the year before. 20th December 1988 saw a record low temperature in central Greece (http://weatherspark.com/history/32209/1988/Dervenochoria-Central-Greece)

1989-10-05 06:00:00 No.:1751





1988-12-16 12:00:00 No.:1634





Evaluate close matches

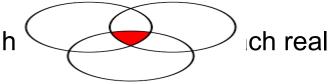
Frobenius norm F of the distance between candidate and close members

$$||A||_F = [\sum_{i,j} abs(a_{i,j})^2]^{1/2}$$

Dot norm: subtract the vectors, make inner product and average (mean of dot product), np.dot(A.T*A).mean() Here Dot offers an alternative set of close matches

Take top M candidates for each of the 3 distance measures and calculate intersection!

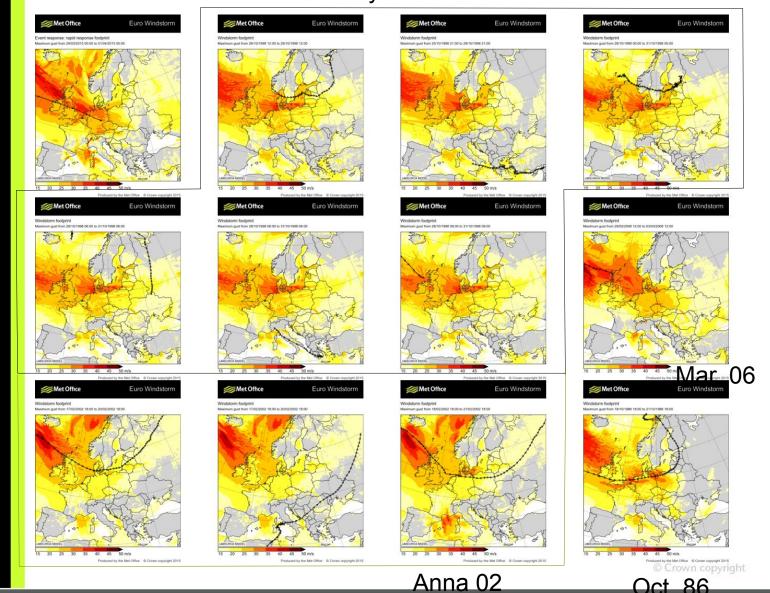
Provide an envelope of similar h time SFP





Niklas

Storm Footprint matches Xylia 96



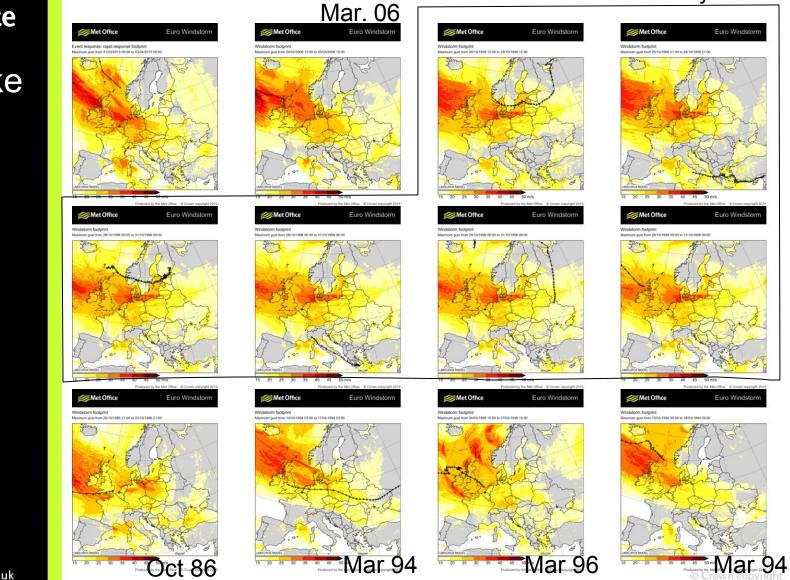
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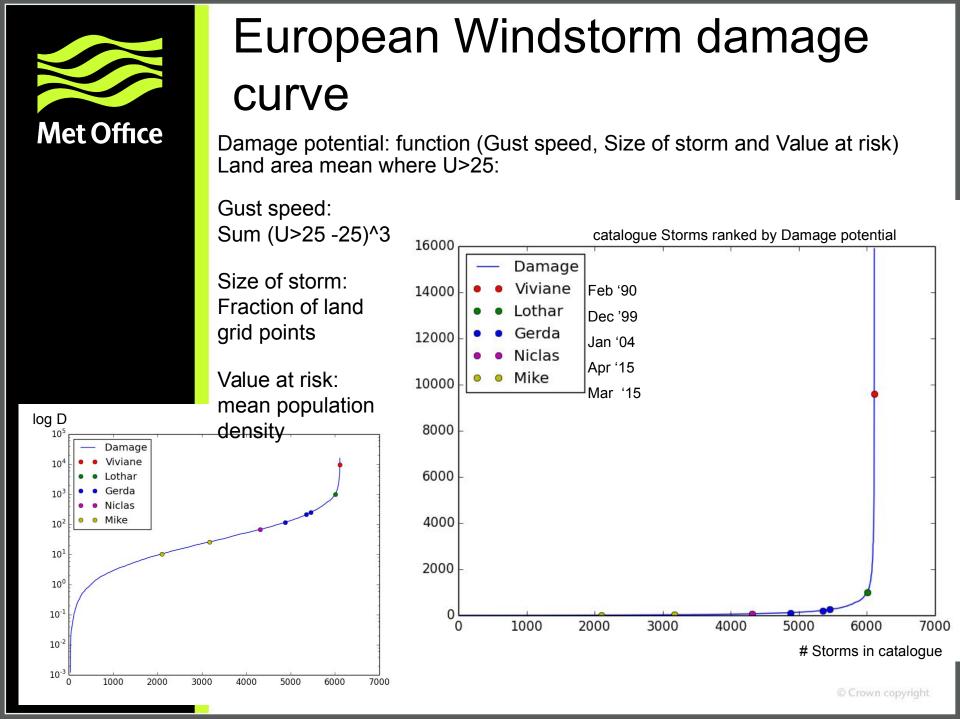
Mike

Storm Footprint matches

Xylia 96



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Storm Footprint matching

Match a recent or predicted SFP with The Historical Windstorm Catalogue By generating a list of features for all catalogue members (one off!) Rank features and pick closest members Evaluate final group of candidates For each real time SFP, provide an envelope of similar historic events.



Apply pattern matching to:

Find similar storms in catalogue

Unpick the strongest/most damaging events (rather than relying on other naming agents)

Prove similarity between catalogue (ERA) and event response (Euro4) for overlapping period (late 2013)

Match event response SFP with appropriate cluster from Catalogue

To gauge impact of predicted event and prepare!



Questions & Answers

www.metoffice.gov.uk/insurance or contact us on peril@metoffice.gov.uk

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p(i,j): (i,j)th entry in a normalized gray-tone spatial dependence matrix, p(i,j) =P(i,j) / R * P(i,j) is the co-occurrence matrix and R is the sum of values in it, thus P(i,j) can be considered as the joint distribution of i and j, which are gray levels of the original image. The value of entry p(i,j) is supposed to be very small due to the large size of the co-occurrence matrix.

- px(i) / py(i): ith entry in the marginal-probability distribution matrix obtained by summing the rows/columns of p(i,j).
- Ng: Number of distinct gray levels in the image.

Used in machine learning context, to analyse medical images, remote sensing, crowd behaviour from surveillance videos, search engines....

Angular Second Moment

Contrast

Correlation

Sum of Squares: Variance Inverse Difference Moment

Sum Average

Sum Variance Sum Entropy

Entropy

Difference Variance

Difference Entropy

Info. Measure of Correlation 1

Info. Measure of Correlation 2

Max. Correlation Coeff.

 $\sum_{i} \sum_{j} p(i, j)^{2}$ $\sum_{n=0}^{N_{g}-1} n^{2} \{ \sum_{i=1}^{N_{g}} \sum_{j=1}^{N_{g}} p(i, j) \}, |i - j| = n$ $\frac{\sum_{i} \sum_{j} (ij) p(i, j) - \mu_{x} \mu_{y}}{\sigma_{x} \sigma_{y}}$

where μ_x , μ_y , σ_x , and σ_y are the means and std. deviations of p_x and p_y , the partial probability density functions

 $\sum_{i} \sum_{j} (i - \mu)^2 p(i, j)$ $\sum_{i} \sum_{j} \frac{1}{1 + (i - j)^2} p(i, j)$ $\sum_{i=2}^{2N_g} i p_{x+y}(i)$

where x and y are the coordinates (row and column) of an entry in the co-occurrence matrix, and $p_{x+y}(i)$ is the probability of co-occurrence matrix coordinates summing to x + y

$$\begin{split} \sum_{i=2}^{2N_g} (i - f_8)^2 p_{x+y}(i) \\ &- \sum_{i=2}^{2N_g} p_{x+y}(i) \log\{p_{x+y}(i)\} = f_8 \\ &- \sum_i \sum_j p(i,j) log(p(i,j)) \\ \sum_{i=0}^{N_g-1} i^2 p_{x-y}(i) \\ &- \sum_{i=0}^{N_g-1} p_{x-y}(i) \log\{p_{x-y}(i)\} \\ \frac{HXY - HXY1}{\max\{HX,HY\}} \\ (1 - \exp[-2(HXY2 - HXY)])^{\frac{1}{2}} \\ \text{where } HXY = -\sum_i \sum_j p(i,j) \log(p(i,j)) , HX , \\ HY \text{ are the entropies of } p_x \text{ and } p_y , HXY1 = \\ &- \sum_i \sum_j p(i,j) \log\{p_x(i)p_y(j)\} HXY2 = \\ &- \sum_i \sum_j p_x(i)p_y(j) \log\{p_x(i)p_y(j)\} \end{split}$$

Square root of the second largest eigenvalue of \mathbf{Q} where $\mathbf{Q}(i, j) = \sum_{k}^{W} \frac{p(i,k)p(j,k)}{p_{x}(i)p_{y}(k)}$