This document outlines our response to the reviewers and the editor and how we have adapted the paper accordingly.

<u>Reviewer 1</u>

1.   This study proposes and tests a methodology to detect a) changes in stream flow, b) discriminate them into different types and c) relate them to changes in meteorological drivers. Key idea is to calculate variograms of log transformed stream flow anomalies for moving window of 5 years and to characterize these variograms based on their partial sill, range, semi variance at a lag equal to 50% of the range and the semivariance averaged over the 3 smallest lag times. Changes in these parameters are defined as significant when dropping outside of the 90 confidence band of the corresponding parameters characterizing the variogram calculated for the full range time series of 30 years. These confidence limits are derived from 1000 bootstraps. After the sensitivity of the methods is demonstrated using artificial test cases, the method is applied to 94 catchments in the UK. Although proposed study addresses an important topic and the results are potentially of high interest, I have major concerns about the proposed method.

Response: The authors would like to thank the reviewer for their insightful comments regarding the use of geostatistical methods in a non-stationary context. These comments reflect issues around using global variograms to provide an absolute description of the temporal autocorrelation of the data. However, this paper is not aiming to provide such an absolute description for the purposes of prediction; rather, we seek to characterise temporal changes in 5 year moving windows relative to the variogram created over 30 years. We have added more detail about the assumptions of the method.

2.   Geo-statistics relies at least on the assumption of weak stationarity, otherwise the nugget + sill are not equal to the total variance. Seems a little difficult to use a method which assumes stationarity to detect non-stationarity. Calculating variograms for five years intervals assumes stationarity within this period, this can be checked based on the distribution of the residuals, which should be uncorrelated in time and standard normally distributed. Is this the case?

Response: It is clearly difficult to test for stationarity as in all cases we only have one realisation of the variogram expressed in the data. However, if one assumes stationarity is present, then the variogram parameters in both the moving windows and the overall variogram parameters should, within some range due to random error, be coincidental. We previously developed something similar for spatial data (see Corstanje et al., 2008), in which we looked at local deviations from a global variogram behaviour. The point here is that we are not trying to ascribe the behaviour in the global variogram as the definitive expression of the autocorrelative structure, but rather we are proposing a method in which we are looking for differences between variograms at different time scales. Where we see such significant differences, then clearly the temporal autocorrelative structure has changed and this may be due to climatic change or changes in the catchment characteristics (including land management). A section has been added to the methods section outlining that we are not aiming to provide the precise autocorrelative structure of the river flow time series.

1

3.   Non-linear transformations (such as the log transformation) destroy the auto covariance structure of the stream flow data, in the sense the original data have a different autocorrelation time. How to infer on changes of the autocorrelation of the original data with the given method?

Response: That is not entirely the case, but is true regarding the relationships between the variance components. It is the relative contribution of the variances that are affected by the transformations (as taking logs stabilises the variance) rather than their temporal dependencies. Again, we are not aiming at providing a precise characterisation of the temporal autocorrelation of the time series, rather, we are examining the change in temporal autocorrelation. These relative changes are indeed determined in a log-transformed environment, but relative to each other. We have adapted the methods section to state that the hydrological data does not need to be logged in order to create a variogram.

4.   Working with anomalies relies again implicitly on stationarity of the mean and variance. If the stream flow data have e.g. a trend in the mean, but you use a constant mean to calculate the anomalies this will appear as trend in variability as the anomalies get larger in direction of the trend.

Response: That is assuming the anomalies are structured and appear more consistently towards a particular period, which in, and of itself, is interesting and precisely what the method is set up to detect. The method is set up to detect relative differences from a postulated mean behaviour. To reiterate, if the underlying catchment is stationary in the mean and variance and the surrounding behaviour is random noise, then the moving window statistics should correspond to the global statistics, and we are dealing with a very un-interesting catchment. If, on the other hand, we find the moving window statistics do not correspond with the overall model, then there is non-stationary behaviour, which would allude to changes in the catchment. We then look for structure in these deviations and try to understand if they are meaningful. These deviations could be related to trends in the mean or the variance.

5.   The presented test cases corroborate that the method attributes trends in the mean or an emergent periodicity (which is trend in where stream flow is expected/ a deterministic pattern) partly to changes in the sill (thus changes in the randomness). This is an intrinsic weakness of the variogram per se when being used in data sets containing trends.

Response: The Sill of a variogram is the sum of the nugget and the variation which is attributed to temporal autocorrelation. There is some discussion in the literature as to whether the nugget is due to random behaviour, or whether it is attributable to behaviour at sampling intervals smaller than that considered in the study. When the variogram is 'pure nugget' then arguably one could attribute the Sill to random behaviour, but if the nugget is smaller than the Sill, then there exists a variance component that is temporally correlated. In response to the concern in that we are attributing meaning to outcomes of a process that is essentially random noise superimposed on a trend, we emphasise that we are considering here the Sill, the Range and other variogram properties. The variogram is a function of the semi variances, which do increase with an increase in magnitude (upwards trend) or decrease with a decrease in

magnitude (downwards trend), and this is one of the properties we wish to pick out for the analysis (in this sense, this is no different to some of the other trend analyses such as the unit root tests − e.g. Augmented Dickey–Fuller test). But beyond the general trend, this method also allows us to determine local changes at key time intervals which general trend analysis would not be able to supply.

<u>References</u>

Corstanje, R., Grunwald, S., and Lark, R. M.: Inferences from fluctuations in the local variogram about the assumption of stationarity in the variance, Geoderma, 143, 123-132, http://dx.doi.org/10.1016/j.geoderma.2007.10.021, 2008.

1.   This paper introduces a new method, applying variogram parameter estimation within moving time windows in order to detect changes in runoff behaviour for 94 UK catchments. The temporal changes are then related to meteorological variables. Also, estimated variogram parameters are related/interpreted to characteristics of the runoff time series. While the first reviewer is strongly criticising the theoretical assumptions of using/estimation variogram in this context, I do not see this point as too much of a limitation. Estimating extreme value distributions within moving temporal windows is pretty standard in order to illustrate how additional uncertainty exists concerning necessary time series length and how derived recurrence intervals might vary dependent on available data. I can easily see the estimated variogram parameters as a temporally changing auto-correlation characteristic that is analysed against some average behaviour – so I am fine with that, but would like to see some uncertainty information on the parameter estimates for each window.

Response: The authors would like to thank the reviewer for their comments.

2.   But before going into detail here, I think there is a more general concern I would like to rise and that I think would need to be discussed (and solved) beforehand. Why are the authors going the tedious way of estimating variogram parameters first, when they later try to relate them to various characteristics of the runoff time serious? Especially when variogram parameter information contain mixed properties of these runoff time series (which are the topic of concern anyway). Why do they not analyse the runoff characteristics directly and try to relate them to meteorological conditions? While it seems interesting to analyze the Meteorology-Variogram-Runoff relationship, it is not obvious to me here why this additional step of variogram analyse has been introduced at all!

Perhaps a comment in the discussion would be able to clarify this point – and I am willing to take arguments into consideration ... however I believe this should be made much clearer (in case there is a good reason) in the paper!!

Response: This paper is part of a larger project aiming to identify how catchment characteristics influence a river response to climate variability. Current ongoing work is examining how catchment characteristics influence how much observed river flow change can be explained by precipitation; the underlying motivation is to explain widely observed heterogeneities in river flow variability. Variograms are used in earlier work by the same authors (Chiverton et al, 2015), showing that the shape of the global variogram is a useful analogue for the precipitation-to-river flow relationship which is moderated by catchment characteristics. Therefore it is hypothesised that changes in the shape of the variogram over time are also influenced by the catchment characteristics.

This work needed to establish how precipitation characteristics influence the different variogram parameters and how much of the temporal changes can be described by precipitation alone. This enables the next part of the work to evaluate if the catchment characteristics influence the amount of temporal variability in the variogram parameters which is explained by precipitation. Hence, our initial motivation to use variograms was

influenced by the wider study framework, but in undertaking this investigation we believe we have demonstrated that the variogram approach has significant potential for wider application to change detection when applied to hydrological time series.

Uncertainty in the variogram parameters

The relative goodness of fit was looked at for each moving window. However, because there is only one realisation of the variogram for the data, calculating uncertainty estimates would require running Monte Carlo simulations for each moving window for every catchment (over 2,500 simulations). This would be a considerable endeavour and would certainly constitute an interesting follow-on from the current study. We note in the paper that there will be uncertainty around the parameter estimates but we consider here the relative difference between the estimates and place less value in the absolute numbers. We have now carried out a stability test in order to verify if the changes detected in the TSV method are caused by a change in the autocorrelation structure or by a few extreme points influencing how the variogram model fits the data.

Why use variogram parameters?

The question of why to use variograms was also asked by reviewer 3. When thinking about why the paper has used variograms, perhaps it is indeed more appropriate to think of the variogram parameters as indicators of river flow. However, as a composite indicator of a range of potential changes in flow dynamics, the variogram does have some advantages for use in change detection. Firstly, variograms can detect changes which other indicators may not be able to (e.g. changes in variability at a range of scales). Secondly, as the reviewer points out, a variogram provides information about a mixture of properties in the river flow time series (e.g. standard deviation, seasonality, linear trends). Therefore using variograms provides an approach which does not rely on the user extracting a pre-conceived aspect of the river regime (e.g. high or low flows) selected for each month/year/season of interest, and conducting trend analysis. The variogram approach takes the correlation structure of the entire river flow series and uses the emergent variogram parameters as an efficient way of summarising variability in each window. Therefore, this prevents the disregarding of much of the data which occurs when calculating some indicators (e.g. 7 day min or max).

However, if the desire of the user is to investigate a specific aspect of the river flow then this may not be the most appropriate method. The paper has been be re-worded to acknowledge that the variogram can be considered as an indicator of river flow (characterising the temporal dependence) and we have pointed out that (as with any change detection technique) it depends on the user's needs as to whether this method is appropriate. More material about the specific merits of the variogram has been added along with an explanation that the TSV technique will not be appropriate for all needs.

With regards to the comment of why add an extra step between precipitation and river flow (precipitation-variogram-river flow), we did not intend there to be an extra step. We see this study as precipitation – river flow, but with the variogram being used to characterise river flow. Our intention of the particular periods of river flow in the discussion was to provide an (albeit descriptive) evaluation of how well the TSV approach captured changes in river flow

variability that have previously been characterised using more simple indicators of seasonal and annual flows, or high/flow indicators. Variograms have not been used before to identify temporal changes in river flow dynamics, so we spend some time corroborating the TSV results with known river flow changes. This motivation behind our discussion has been made clearer in the paper. It is important to note that the discussion does go beyond validation, as we also shed new light on the meteorological drivers of known periods of river flow volatility. There has been widespread interest in questions of whether hydrological extremes have become more severe/frequent in the recent past, but some of these recent periods have been characterised by pronounced variability across the full flow range. Our new approach provides a way to characterise this volatility efficiently and to link it to changes in particular rainfall characteristics. We have explained why river flow data is included in the discussion (as an evaluation of the TSV method).

References

Chiverton, A., Hannaford, J., Holman, I., Corstanje, R., Prudhomme, C., Bloomfield, J., and Hess, T. M.: Which catchment characteristics control the temporal dependence structure of daily river flows?, Hydrological Processes, 29, 1353-1369, 10.1002/hyp.10252, 2015.

Reviewer 3

1. This paper introduces the temporal variogram as a tool to detect changes in streamflow variability. This is achieved by analyzing the changes in specific characteristics of the temporal variogram applied to moving windows. I think the paper could be improved by (i) citing more literature to give wider back- ground; and (ii) clarify the motivation and the aims for the paper.

Response: We would like to thank the reviewer for their comments on our paper.

2. The cited literature on detecting trends and changes in environmental time series is too limited. It is not enough to state that in most studies Mann-Kendall test is used. Other trend tests that are less sensitive to start and end points are used (e.g. Stahl et al, 2010). Detection of one or several change points in mean and/or variance is studied in many papers (e.g. Raje, 2014; Sefidmazgi, 2014; Jandhyala, et al, 2013; Beaulieu et al 2012; Toreti et al, 2012). Also the links between changes in meteorological characteristics and streamflow response is studied (e.g. Kumar and Duffy, 2009). I therefor think the authors should include more relevant literature and show how the proposed method fits into a wider background than what is currently in the paper. Since the paper already has a link to geostatistics, you might also refer to literature on detecting spatial non-homogeneities (e.g. Darbeheshti and Featherstone, 2014; Atkinsona and Lloyd 2007).

Response: The background literature has been extended to mention some of the other change detection methods which are used for hydrological data. However, as I am sure the reviewer is aware, change detection in hydrology is a huge research area and this cannot be reflected in an introduction. With regards to the method used in Stahl et al (2010), both the paper and a follow up paper (Hannaford et al, 2013) identified that both the magnitude and direction of change are influenced by the start and end dates, with the Thiel-Sen estimator as well as the Mann-Kendall test. This sensitivity to study period is widely acknowledged in the change detection literature, as clear from a range of reviews of the topic (e.g. Hall et al. 2014, cited in our paper, and references therein).

3. Concerning the motivation of the paper, I feel that there is a limited coherence between the suggested limitations of traditional methods (e.g. not able to tell when a change takes place, to sensitive to period of data, only indices are analyzed), the proposed methodology, and the final results. It would be useful if you demonstrate more explicitly how the proposed methods meet these challenges. I also think that the argument that "the method is based on raw daily flows and requires no pre-calculated indicators (e.g. annual or seasonal averages, minimum or maximum flow" is misleading since the paper actually analyze changes in "variogram parameters" that also might be used as indicators. Any kind of statistics and/or indicators, also Q95, could be calculated within sliding windows, not only variogram statistics. It would also be useful to more explicitly write out which changes it is important to detect (in this paper), and how they are detected based on the proposed methodology. Like reviewer II, I am not convinced that the variogram parameters are the best tool to detect these changes. Then more specific statistical tests for changes i trends and/or variability, changes in

seasonality, might be more useful. Any kind of statistics could be calculated within sliding windows, not only variogram statistics.

Response: In terms of the motivation to the paper (why use variograms?), I would like to refer to our response to reviewer number 2. We have clarified in the paper that we are detecting changes in the temporal dependence which can be thought of as an indicator of river flow. Temporal dependence is influenced by several aspects of the flow regime (identified by applying artificial changes to the river flow in Figure 4). We agree that any kind of statistic can be calculated in moving windows, and indeed they often are; but that entirely depends on the purpose of the study – Q95 would clearly be more low flow focused, for example. Our study does not set out to detect changes in extremes, rather we examine changes in variability (over a range of timescales) and temporal dependence, which the variogram captures well. We tried to set out our motivation in the introduction, but we agree that we may have focused more on identifying the weaknesses of existing approaches rather than specifying the rationale for our variogram-based approach. We have added more clarity to this, as stated also in the reply to reviewer 2.

4.   Variogram estimation does not necessarily depend on the data to be normally distributed. However, if you want to interpolate, the normality of data becomes important. Log-transformation will also help to reduce the effects of high outliers. In many studies, i.e. on rainfall, variograms are estimated directly from raw data (e.g. Leblois and Creutin; 2013). The tranformation of data will affect the shape of the variogram, the nugget and sill, but not (or maybe less) the range. E.g. Leblois and Creutin (2013) show how an "anamorphosis function" for the variogram might be estimated when the transformation HESSD is known. In this study the log-transformation will most likely increase the covariance for the shortest time lags.

Response: With regards to the data transformation, as the reviewer notes, logging the data reduces the amount of variability and enables a better fit for the variogram models. A more detailed explanation is provided in the response to reviewer 1. The paper has been adapted to state this and highlight that daily river flow data does not necessarily need to be logged.

5.   Please state explicitly the time resolution of data used in the study.

Response: The time resolution of the hydrological data (daily) has been stated in the paper.

6.   Page 11767, line 10: It is written: "In terms of change detection, the key advantages of variograms are: the method is based on raw daily flows" This is confusing since "raw daily flows" are not used in the paper.

Response: The statement "In terms of change detection, the key advantages of variograms are: the method is based on raw daily flows" has been changed to "In terms of change detection, the key advantages of variograms are: the method uses the whole daily river flow time series"

7.   Page 11767: It is written: "In terms of change detection, the key advantages of variograms are: the method is based on raw daily flows and requires no pre-calculated indicators (e.g. annual or seasonal averages, minimum or maximum flow); both linear and nonlinear changes can be detected; the identified change is in relation to expected flow dynamics which represent the whole time period, not just the start and end of a given period; and the dynamics of the river flow time-series can be analysed as changes in variogram parameters relate to changes in different aspects of the river flow regime" I am a bit confused if this is a statement, conclusion, or a hypothesis. If it is a statement, I would like to see more arguments and maybe references, if it is a conclusion it should not be here, and if it a working hypothesis, it need to be reformulated.

Response: In a sense, the paragraph that the reviewer highlights was where we have tried to argue the rationale behind using variograms. But in hindsight we agree that this is worded a bit more like conclusion/discussion and so doesn't sit well here. We have added more detailed information on our motivation and some background to why variograms are an appealing avenue, in the introduction, and have saved the more detailed material on the merits of the approach to the discussion.

8.   Page 11770 First lines: Exactly which frequencies were removed

Response: The frequencies removed during the de-seasonalising are catchment dependent. The frequencies are fitted using the deseasonalize package in R, this has been stated in the paper. This is a standard approach described in Hipel and McLeod (1994) and Chandler and Scott (2011).

9.   Page 11770 line 13: I suggest to write: "Based on the transformed, de-seasonalized standardized flow data".

Response: Page 11770, line 13 has been changed to the reviewers recommendation of "Based on the transformed, de-seasonalized standardized flow data".

10.   Page 11770, line 23: Does actually any nugget-effects appear using this data set? If you have daily data, no uncertainty included, I would guess that the empirical nugget is zero.

Response: The Nugget is approaching zero, particularly in groundwater dominated catchments, however, it is not zero and this has been mentioned in the paper (see also our replies to reviewer 1 in relation to the Nugget and the Sill).

11.   Page 11772 line 5-10: How large is the time shifts between the moving windows (1 day or 1 year?)

Response: The time shifts are 1 year and this has been stated in the paper.

12.   Page 11773 The paragraph starting on line 24 is not easy to capture.

Response: We have changed the paragraph from: "Autocorrelation is present in the variogram parameter time-series. Whilst this will not influence the amount of bias or consistency of the precipitation characteristics, positive autocorrelation will influence the efficiency of the explanatory variables and therefore overestimate the significance. However, analysing the residuals (using the Durbin-Watson test for autocorrelation disturbance) showed no significant autocorrelation. Therefore, regressing against several precipitation variables with similar autocorrelation to the variogram parameters (both averaged over five year moving windows) series adequately removes the autocorrelation."

To: "Positive autocorrelation would influence the efficiency of the explanatory variables causing an overestimation the significance. However, analysing the residuals from the MLR between precipitation and river flow (using the Durbin–Watson test for autocorrelation disturbance) showed no significant autocorrelation. Therefore, it is deemed that, regressing against several precipitation variables with similar autocorrelation to the variogram parameters (both averaged over five year moving windows) series adequately removes the autocorrelation."

13.   Page 11780: Could temperature be a meteorological factor that is not accounted for? If snow accumulation and snow melt occurs in some of these catchments, it could be very important.

Response: Temperature and hence evapotranspiration could be indeed important factors which are not included in the MLR model. We did include soil moisture deficit (which accounts for evapotranspiration to a degree) in an earlier version, but it was not felt to be meaningful when calculated over long windows. Additionally snow could be important in some years, particularly in upland catchments. At 11780, L11, we note that other meteorological characteristics could be important. We have added more detail on the possible importance of evapotranspiration and snow as an avenue for further work.

References

Atkinsona, P.M, C.D. Lloyd (2007) Non-stationary variogram models for geo- statistical sampling, Journal of Spatial Science, 55(2) Pages 185-204 DOI: 10.1080/14498596.2010.521971

Beaulieu, C.a , Chen, J.b, Sarmiento, J.L.a (2012) Change-point analysis as a tool to detect abrupt climate variations, Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 370, 1228-1249

Chandler, R., and Scott, M.: Statistical Methods for Trend Detection and Analysis in

the Environmental Sciences, John Wiley and Sons, Ltd, Chichester, West Sussex, 367 pp., 2011.

Darbeheshti, N. , Featherstone, W.E. (2014) A review of non-stationary spatial methods for geodetic least-squares collocation optimisation: An empirical investigation using elevation data, Computers & Geosciences 33 (2007) 1285–1300,

doi:10.1016/j.cageo.2007.05.011

Gorji Sefidmazgi, M., Sayemuzzaman, M., Homaifar, A. , Jha, M.K., Liess, S (2014) Trend analysis using non-stationary time series clustering based on the finite element method, Nonlinear Processes in Geophysics, 21(3), 605-615

Hall, J., Arheimer, B., Borga, M., Brázdil, R., Claps, P., Kiss, A., Kjeldsen, T. R., KriauciÅnnienÄ U, J., Kundzewicz, Z. W., Lang, M., Llasat, M. C., Macdonald, N., McIntyre, N., Mediero, L., Merz, B., Merz, R., Molnar, P., Montanari, A., Neuhold, C., Parajka, J., Perdigão, R. A. P., Plavcová, L., Rogger, M., Salinas, J. L., Sauquet, E., Schär, C., Szolgay, J., Viglione, A., and Blöschl, G.: Understanding flood regime changes in Europe: a state of the art assessment, Hydrol. Earth Syst. Sci. Discuss., 10, 15525-15624, 10.5194/hessd-10-15525-2013, 2013

Hannaford, J., Buys, G., Stahl, K., and Tallaksen, L. M.: The influence of decadal-scale variability on trends in long European streamflow records, Hydrol. Earth Syst. Sci., 17, 2717-2733, 10.5194/hess-17-2717-2013, 2013.

Hipel, K. W., and McLeod, A. I.: Time Series Modelling of Water Resources and Environmental Systems. Elsevier, Toronto, Canada, 1013 pp., 1994.

Jandhyala, V.a , Fotopoulos, S.a, Macneill, I.b, Liu, P.c (2013) Inference for single and multiple change-points in time series, Journal of Time Series Analysis, 34(4), 423-446

Kumar, M., Duffy, C.J. (2009) Detecting hydroclimatic change using spatio-temporal analysis of time series in Colorado River Basin, Journal of Hydrology, 374(1-2), 1-15

Leblois, E., and J.-D. Creutin (2013), Space-time simulation of intermittent rainfall with prescribed advection field : Adaptation of the turning band method, Water Resour. Res., 49, 3375–3387, doi:10.1002/wrcr.20190.

Stahl, K., H. Hisdal, J. Hannaford, L. M. Tallaksen, H. A. J. van Lanen, E. Sauquet, S. Demuth, M. Fendekova, and J. Jodar (2010) Streamflow trends in Europe: evidence from a dataset of near-natural catchments, Hydrol. Earth Syst. Sci., 14, 2367–2382, doi:10.5194/hess-14-2367-2010

Raje, D. (2014) Changepoint detection in hydrologic series of the Mahanadi river basin using a fuzzy Bayesian approach , Journal of Hydrologic Engineering, 19(4) 687-698

Toreti, A , Kuglitsch, F.G., Xoplaki, E., Luterbacher, J.R. (2012) A novel approach for the detection of inhomogeneities affecting climate time series, Journal of Applied Meteorology and Climatology, 51 (2), 317-326

Response to the editor

1.   The referees have raised several issues that need to be taken into consideration in a revised version of the paper. Generally, your replies to the referee's comments sufficiently consider these issues and I encourage you to revise your manuscript accordingly.

Response: We would like to thank the editor for their comments**.**

2.   Especially, please address the point of referee #2 with respect to providing some uncertainty/stability estimate of the variogram parameters within each time window (e.g. with a split-sampling test within the time window, or by making the time-windows overlapping): This will be an important prerequisite to evaluate the relevance of changes of the variogram parameters between the time windows.

Response: Addressing the point reviewer 2 made about uncertainty analysis. We have carried out a stability test in order to verify if the changes detected in the TSV method are caused by a change in the autocorrelation structure or by a few extreme points influencing how the variogram model fits the data.

3.   Also, please pay special attention to the comment of referee #3: make more clear the differences and advantages of your variogram-based approach compared to analysis of time series of alternative signatures derived from moving-windows (as the referee correctly states, the moving-window approach could be applied to any signature). In this context, please also refer to the existing literature on 'classical' approaches of time-series analysis (AR, MA, ARIMA, etc.), which essentially do the same as your variogram approach, i.e. to quantify the temporal autocorrelation structure of a time-series across a range of time-lags. Some related literature is given below.

Response: We have added in more background about other change time series analysis techniques including the classical ARMA suite of approaches and change-point analysis. We have also highlighted the key differences between these approaches and our variogram approach.

References

Chun, K. P., Wheater, H., and Onof, C.: Prediction of the impact of climate change on drought: an evaluation of six UK catchments using two stochastic approaches, Hydrol. Process.,   27,   1600-1614,   2013.

Montanari, A., Rosso, R., and Taqqu, M. S.: Fractionally differenced ARIMA models applied to hydrologic time series: Identification, estimation, and simulation, Water Resources Research,   33,   1035-1044,   1997.

Yang, G. X. and Bowling, L. C.: Detection of changes in hydrologic system memory associated with urbanization in the Great Lakes region, Water Resources Research, 50, 3750-3763,   2014.

Box, G. E. P., and G. M. Jenkins, Time Series Analysis: Forecasting and Control, revised ed., Holden-Day,   Merrifield,   Va.,   1976.

Salas, J. D., C. D. Boes, and R. A. Smith: Estimation of ARMA models with seasonal parameters, Water Resour. Res., 18, 1006-1010, 1982.

Using variograms to detect and attribute hydrological change

A. Chiverton[1, 2, 3], J. Hannaford[1], I. P. Holman[2], R. Corstanje[2], C. Prudhomme[1], T M. Hess[2], J. P. Bloomfield[3]

[1] {Centre for Ecology & Hydrology, Wallingford, United Kingdom}

[2] {School of Energy, Environment and Agrifood, Cranfield University, United Kingdom}

[3] {British Geological Survey, Wallingford, United Kingdom}

Correspondence to: A. Chiverton (andchi@ceh.ac.uk)

Abstract

There have been many published studies aiming to identify temporal changes in river flow time-series, most of which use monotonic trend tests such as the Mann-Kendall test. Although robust to both the distribution of the data and incomplete records, these tests have important limitations and provide no information as to whether a change in variability mirrors a change in magnitude. This study develops a new method for detecting periods of change in a river flow time-series using Temporally Shifting Variograms, TSV, based on applying variograms to moving windows in a time-series and comparing these to the long-term average variogram, which characterises the temporal dependence structure in the river flow time-series. Variogram properties in each moving window can also be related to potential meteorological drivers. The method is applied to 914 UK catchments which were chosen to have minimal anthropogenic influences and good quality data between 1980 and 2012 inclusive. Each of the four variogram parameters (Range, Sill and two measures of semi-variance) characterise different aspects of change in the river flow regime, and have a different relationship with the precipitation characteristics. Three variogram parameters (the Sill and the two measures of semi-variance) are related to variability (either day-to-day or over the time-series) and have the largest correlations with indicators describing the magnitude and variability of precipitation. The fourth (the Range) is dependent on the relationship between the river flow on successive days and is most correlated with the length of wet and dry periods. Two prominent periods of change were identified: 1995 to 2001 and 2004 to 2012. The first period of change is attributed to an increase in the magnitude of rainfall whilst the second period is attributed to an increase in variability in the rainfall. The study demonstrates that variograms have considerable potential for application in the detection and attribution of temporal variability and change in hydrological systems.

1. Introduction

Increasing scientific agreement on climate change (IPCC, 2013) has been paralleled by a rise in the number of studies investigating the potential impacts on various aspects of the earth system, economies and society. One projected impact from climate change is a change in river

16

flow dynamics, in particular changes in the magnitude, seasonality and variability of river flows which could have major impacts on the management of water resources and flood risk (e.g. Hirabayashi et al. (2013) and Gosling and Arnell (2013)) on a global scale. For the UK the potential impact of climate change on water resources and flooding has recently been reviewed by Watts et al. (in press). Examining future changes in river flow is a focus for many modelling studies. However, the uncertainties inherent in ~~the~~ scenario-based future projections (Prudhomme et al., 2003) highlight the need for observational evidence of change (Huntington, 2006).

Being able to detect and attribute changes in observed data is challenging, particularly in systems which are the result of complex, often non-linear, interactions between several processes (e.g. precipitation, evapotranspiration, storage and transport within a catchment). Further levels of complexity are added due to temporal changes in catchment characteristics (e.g. land cover and land management), anthropogenic modification of rivers (e.g. abstraction, impoundments and channel modifications) and changes in the location and hydrometric performance of gauging stations.

Previous studies have shown trends of increases and decreases in observed river flow for individual catchments, but at the regional to national scale the picture is more complex and regional patterns are often not spatially coherent (as noted for Europe, e.g. Kjeldsen et al. (2014)) and results are dependent on the methods and the study periods used. In the UK, significant heterogeneity in streamflow trends has been reported, with trends of different sign occurring in catchments in close proximity (Hannaford and Buys, 2012). These spatial and temporal differences in published results of change detection studies are an obstacle to efforts to develop appropriate adaptation responses, particularly when there is a lack of congruency with scenario-based projections for the future. This has led to calls for fresh approaches to change detection, as highlighted by several recent synthesis reviews (e.g. Burn et al. (2012); Merz et al. (2012); Hall et al. (2013)) and the IAHS decade 'Panta Rhei' ('everything flows') which aims to reach an improved understanding of the changing dynamics in the water cycle (Montanari et al., 2013). This paper describes one such new avenue for change detection, namely Temporally Shifting Variograms.

1.1. Review of previous approaches to change detection

Detection of environmental change is a huge area of research which cannot easily be reflected in an introduction. More extensive reviews of change detection methods in hydrology are available (e.g. Yue et al. (2012)) and there are textbooks on trend testing in the environmental sciences in general (e.g. Chandler & Scott, 2011). The overview below will give the reader a flavour of the range of methods which are avaliable, with a brief critique, to set the new method described in 1.2 in context. The choice of change detection method clearly depends on the users' aims and available data.

The majority of these hydrological change detection studies use monotonic trend tests such as Mann-Kendall (details of which can be found in Yue et al. (2012)) which are influenced by the amount of autocorrelation in the data as well as by the start and end points of periods to which the trends tests are applied (Hannaford et al. (2013) and Chen and Grasby (2009)). This is particularly problematic when the gauging stations have relatively short records starting in a relatively dry or wet period. For example, the UK gauging station network was largely built in the 1960s when the North Atlantic Oscillation Index (NAOI) was in a strong negative phase resulting in conditions for the UK which were drier than much of the following record. Furthermore, monotonic trend tests only provide information as to whether change has occurred over the time-period being investigated and no information is gained as to the type (e.g. abrupt or gradual) or the timing of change. This is a major limitation as it makes it difficult to link a simple monotonic trend in streamflow to trends in potential drivers of change (i.e. changes in meteorological conditions or catchment properties). A further weakness of current change detection methods is that they often use indicators of flow selected *a priori* to characterise a particular aspect of the flow regime (e.g. the Q_{95}; 7-day minimum flow; frequency of Peaks-Over-Threshold, etc), which potentially introduces bias by selecting a pre-determined aspect of the flow regime.

Another approach to change detection is change-point analysis, which can be used to identify the temporal location where change occurs (e.g. Beaulieu et al. (2012) applied change-point analysis to climate variables and Jandhyala et al. (2013) reviews change-point analysis including a plethora of studies which investigated change-points in the Nile river flow time series). Change-point analysis identifies the temporal location at which one or more properties of the river flow time series change abruptly (e.g. a change in the magnitude, variability or

autocorrelation, etc), but are associated with several limitations. Firstly, there is increased uncertainty about change-points detected close to the start or end of the time series (due to a higher risk of false detection). Secondly, the method only detects one aspect of the time series (e.g. changes in linear trend, magnitude, variability or autocorrelation). Finally, although change-point analysis is designed to detect abrupt changes there is, in practice, great difficulty in discriminating between trends and abrupt changes (as demonstrated by Rougé et al. (2013). Jarušková (1997) provides a cautionary review of change-point detection methods for river flow data.

An alternative approach to change detection is through analysis of periodicities. There is a wide range of methods available for decomposition of time series into various components (e.g. Fourier methods, Empirical Mode Decomposition, Wavelets; see for example Labat (2005) and Sang (2013)). These approaches can detect complex non-linear patterns of variability and do not require the selection of indicators as they are normally based on the whole time series. However, such approaches normally characterise periodicities over a range of scales, rather than changes over time. It is hard to relate the change in spectral shape to the hydrological regime (Smith et al., 1998). This is indicated by recent studies in the UK which applied these methods and did not go beyond looking at the high-level drivers, particularly the NAOI (e.g. Sen (2009) and Holman et al. (2011)). Similarly, Kumar and Duffy (2009) use single spectral analysis to look at the precipitation – temperature – river flow relationship. This analysis enabled the authors to link the identified temporal changes to the southern oscillation as well as large anthropogenic influences (dam building and pumping), but did not investigate how changes in different aspects of the precipitation regime (e.g. seasonality and magnitude) influence the river flow time series.

1.2. The proposed new method

In the light of weaknesses with conventional change detection methods, there is a need for new approaches which can give more insight (going beyond a single value for change) into how river flow dynamics evolve through time, in a way that dispenses with fixed study periods and pre-determined flow indicators and thereby allows The need for fresh approaches to change detection has been highlighted by several recent synthesis reviews (e.g. Burn et al. (2012); Merz et al. (2012); Hall et al. (2013)) and is all the more timely and relevant considering the IAHS decade 'Panta Rhei' ('everything flows') which aims to reach an

~~improved understanding of the changing dynamics in the water cycle (Montanari et al., 2013).~~ ~~streamflow changes to be linked explicitly with external drivers (e.g. meteorological forcing).~~ Here a novel and fundamentally different methodology for detection of hydrological change is introduced using variograms that are applied to moving windows in a river flow time-series (hereafter, Temporally Shifting Variograms, TSV_s) ~~is introduced~~. The TSV method gives insights into how river flow dynamics evolve through time, without relying on fixed study periods or pre-determined flow indicators. This enables streamflow changes to be linked explicitly with external drivers (e.g. meteorological forcing). Variograms are able to capture the temporal dependence structure of the river flow (i.e. on average, how dependent river flow on a particular day is on river flow on the preceding days). The temporal dependence structure is closely related to the amount of variability at different temporal scales in the time series and, as it ~~The temporal dependence structure~~ is influenced by catchment characteristics (Chiverton et al., 2015) it ~~and~~ enables inferences to be made about the precipitation-to-flow relationship in a catchment.

As previously noted in the introduction there are several methods of identifying temporal changes in river flow and a large range of indicators which could also be investigated using a moving window. The TSV has additional key advantages over existing methods. Firstly, ~~In terms of change detection, the key advantages of variograms are~~: ~~the method is based on~~ the variogram can be thought of as a composite indicator which provides information about a range of aspects in the river flow time series, hence enabling a range of possible temporal changes in river flow dynamics (e.g. standard deviation and seasonality) to be captured. Variograms can also detect changes in daily river flow which other indicators may not be able to (e.g. changes in variability at a range of time scales). Furthermore the variogram is calculated using ~~raw~~ daily flow ~~datas~~ and does not rely on the user extracting pre-conceived aspects of the river flow regime via the ~~requires no pre-calculated~~ calculation of indicators (e.g. annual or seasonal averages, minimum or maximum flow). This enables the whole flow regime to be investigated, rather than much of the daily flow information being discarded, as is the case when calculating some indicators (e.g. annual 7 day minimum flow).

It is worth noting that there are a range of stochastic techniques which can characterise the basic autocorrelation structure of data (e.g. AR, ARIMA, etc). These classical time series analysis approaches have been widely used to investigate hydrological behaviour (e.g. Salas et al. (1982), Montanari et al. (1997), Chun et al. (2013)). Such approaches characterise

temporal dependence and can also in principle be applied in moving windows (e.g. AR1 applied in 20-year moving windows by Pagano and Garen (2005)). A limitation with the classical models is that the user has to select the appropriate AR and MA parameters, a potentially subjective process, which will vary between catchments. In practice, they have not been widely used to examine changes in temporal dependence through time.

The method we propose uses variograms to characterise the autocorrelation so that the AR parameter does not need to be specified. Furthermore, variograms are designed to handle missing data which is common in river flow time series. The variogram has several defined parameters (e.g. Nugget, Sill and Range) which characterise different aspects of the autocorrelation structure that can be used in window change analysis. This enables changes in several aspects of the river flow regime to be analysed.

; both linear and non-linear changes can be detected; the identified change is in relation to expected flow dynamics which represent the whole time period, not just the start and end of a given period; and the dynamics of the river flow time-series can be analysed as changes in variogram parameters relate to changes in different aspects of the river flow regime.

Conventionally most trend analysis studies focus on change detection, and attribution is often based on qualitative reasoning and relies on published work to support the hypothesis (Merz et al., 2012). The TSV method enables changes in river flow (associated with changes in variogram parameters) to be quantitatively related to meteorological characteristics. In this sense, tThis work is an attempt to provide a formal 'proof of consistency' (Merz et al. 2012) that river flow changes can be associated to changes in meteorological drivers. This is an important new development, as few published studies of streamflow change have sought to explain observed patterns through links to precipitation. We acknowledge that this does not amount to full attribution without 'proof of inconsistency' with other drivers (e.g. land use change), but it does provide a solid foundation for such attribution studies. and, inIn principle, the method could be used with a wider range of drivers, both natural and anthropogenic, if temporal data on, e.g. land-use change, were also available.

This study has the following objectives: develop a novel change detection method (TSV) to detect both linear and non-linear changes throughout the river flow regime; test the performance of the method by imposing artificial changes to a river flow time-series; identify patterns of temporal change in rivers for a set of 94 catchments in the UK; and explain the

contribution of precipitation to the detected variability in variogram parameters. This paper is structured as follows: section 2 describes the data employed; section 3 details the TSV method; section 4 tests the TSV method using an artificially perturbed river flow time-series; section 5 identifies the periods of change across the 94 UK catchments and section 6 investigates the meteorological drivers.

2. Data

2.1. Catchment selection

Near-natural UK benchmark network catchments, with only modest net impacts from artificial influences, were chosen (Bradford and Marsh, 2003). These catchments are deemed to have good data quality and therefore artificial influences will be limited. Furthermore, only catchments with a record length of 33 years or more (1980 – 2012) of daily river flow data and with less than 5% missing data were considered. Nested catchments with similar flow regimes were also excluded.

This data set was used in a previous study which classified UK catchments into four classes according to their average temporal dependence structure (Chiverton et al. 2015). One of these classes was excluded from the present study; this. This comprises catchments which have high infiltration and storage, hence with distinctly different precipitation-to-flow relationships that the rest of the catchments. In particular, Chiverton et al. (2015) demonstrated that these catchments have a very long range of temporal autocorrelation of over a year, largely due to the influence of groundwater storage, instead of weeks to a few months like the other catchments. To avoid this very different catchment response time overly influencing results, catchments which overlay highly productive aquifers were removed (mainly in the SE of England). This resulted in 94 catchments, shown in Figure 1.

2.2. Precipitation characteristics

Daily catchment-averaged precipitation values were calculated from CEH-GEAR, a 1km^2 gridded precipitation dataset (Tanguy et al., 2014) derived using the method outlined in Keller et al. (2015). From this data, and a range of precipitation characteristics which represent different aspects of the precipitation regime were calculated (Table 1).

3. The Temporally Shifting Variograms methodology

Before going into the details of the method it is important to point out that this paper is not aiming to ascribe the behaviour in the global variogram as the definitive expression of the temporal dependence structure. This paper develops a method which identifies differences between variogram parameters at different time scales that represent significant changes in the temporal dependence structure that are due to meteorological drivers (or, theoretically, anthropogenic influences e.g. land management change, although this is not considered here; see also Section 6).

The methodology consists of four steps, as follows: transformation of river flow data into a form amenable tofor analysis using variograms (setion 3.1); creation of variograms for each catchment (section 3.2); detection of periods of change in streamflow using TSV (section 3.3); and, finally analysis of the influence of meteorological drivers using Pearson correlation and multiple linear regression methods (section 3.4).

3.1. Data transformation

An overview of how the river flow time-series has been de-seasonalised and standardised (steps 1 to 5) is provided here, but in-depth discussion can be found in Chiverton et al. (2015).

1) The river flow data were in-filled, using the equipercentile linking method (Hughes and Smakhtin, 1996), to remove periods of missing data. This was required to improve the de-seasonalisation (step 3).

2) A log-transform of the time-series was undertaken to stabilise the variance and create a near normal distribution. Values of zero were replaced by 0.001 m^3s^{-1} prior to transformation. It should be noted that a variogram could be created for a river flow time series which has not been logged, however, the user would need to take care in the fitting to ensure: a) the variogram fits the data well and b) the shape of the variogram is not overly influenced by extreme values.

3) Seasonality was removed using Fourier representation. This was done to avoid exaggerating the temporal dependence. The de-seasonalising was carried out using the 'deseasonalize' package in R, see Hipel and McLeod (2005) and Chandler and Scott (2011) for further details and illustrative examples.

4) The in-filled data from step 1 wereas removed. The in-filled data wereas solely used for the de-seasonalisation (step above). Since the in-filled data areis associated with a greater uncertainty than the measured data, they and are removed from the subsequent analysis, as variograms are well suited to handling missing data.

5) Flow data ~~have been~~were standardised for each catchment by subtracting the mean and dividing by the standard deviation of the time-series. Standardising enables comparison of catchments with different magnitudes of flow.

3.2. Creating variograms

The temporal dependence structure can be represented by a one-dimensional temporally averaged variogram (see Chandler and Scott (2011) or Webster and Oliver (2007) for detailed background about variograms). Based on the transformed, de-seasonalised standardised flow data, an empirical semi-variogram was calculated for each catchment using the average squared difference between all pairs of values which are separated by the corresponding time lag (Equation 1 which calculated the semi-variance):

$$\hat{v}(h) = \frac{1}{2(\mathbf{N-h})} \sum_{i=1}^{\mathbf{N-h}} [(Y(t_{i+h}) - Y(t_i))^2]$$

Where **h** is the lag time, $Y(t_i)$ is the value of the transformed data at time t_i and (**N-h**) is the number of pairs with time lag **h**.

A variogram model was then fitted (using the variofit function from the geoR package in R and the Cressie method (Cressie, 1985)) to the empirical semi-variogram to enable the following parameters to be calculated (Figure 2): the Nugget, which is the *y* intercept, represents a combination of measurement error and sub-daily variability; the Sill is defined as the semi-variance where the gradient of the variogram is zero. A zero gradient indicates the limit of temporal dependence and is an indicator of the total amount of temporally auto-correlated variance in the time-series. The Partial-Sill is the Sill minus the Nugget and shows the temporally dependent component, used herein as the Sill. The Range is the lag time at which the variogram reaches the Sill value. Autocorrelation (gradient of the variogram) is essentially zero beyond the Range. The Practical-Range is the smallest distance beyond which covariance is no more than 5% of the maximal covariance (time it takes to reach 95% of the Sill) (Journel and Huijbregts, 1978). As the variogram is only asymptotic to the horizontal line which represents the Sill, the Practical-Range is used herein as the Range.

3.3. Detection of change in streamflows using TSV

The fundamental premise of the TSV approach is that variograms are applied in moving windows through a time-series, to determine the extent to which variogram properties (which characterise the autocorrelation structure) change through time. To examine how unusual these changes are in the context of the observed streamflow record, the method determines whether variogram properties in each moving window are outside thresholds which encompass the 5 – 95% range of expected values based on the original 30-year average variogram. Periods of change (compared to the 30-year average variogram) were thus detected for the 94 catchments using the following method, applied to each catchment:

1) Compute bootstrap parameter estimates from multiple realisations of the 30-year average variogram, which are created by simulating 1,000 standardised river flow time-series assuming a Gaussian random field model (see Havard and Held (2005) for more detail). The data were simulated using the model parameters from the original 30 year variogram, so the output has the same lags as the original data (i.e. daily). A variogram was then created for each of the time-series.

2) Calculate upper and lower thresholds (the 5th and 95th percentiles of the 1,000 variograms). Several thresholds were tested and the 5th and 95th percentiles were chosen as these were found to detect an appropriate number of threshold exceedences throughout the time-series.

3) Calculate parameters (see below for details) for variograms applied to five year overlapping moving windows (shifting by one year) from the original (de-seasonalised and standardised) river flow data. The values for the five year moving windows were compared to the range of expected values (between the 5th and the 95th percentiles) for the 30-year average variogram to see if they were above, below or inside the thresholds. Different sized windows between 1 and 10 years were analysed; five year overlapping windows were found to be long enough to obtain a good fitting variogram whilst being short enough not to characterise the average behaviour of the system.

Four variogram parameters were calculated. The Sill and Range were calculated, however, as the data used are relatively high frequency (daily) and good quality, the value for the Nugget is low (although not zero as there is measurement error and sub-daily variability) and the 5th percentile is zero. Therefore, the nugget cannot be handled in the same way as the other variogram parameters (i.e. decreases below the lower bound cannot be investigated). Instead, a new parameter, the 3 Day Average Semi-Variance (3DASV) (average of the first three points of the semi-variogram) was defined and used to investigate changes in very short term temporal dependence. A further parameter was defined, the Half Range Average Semi-Variance (HRASV) (average of the points up to half the Practical-Range) to provide information on the intermediate temporal variability (between the 3 DASV and the Partial-Sill, which is the total amount of auto-correlated variability).

It is acknowledged that there is uncertainty surrounding the variogram calculated from the river flow data. Part of the uncertainty comes from river flow measurement and part from the fitting of the variogram model. Due to the number of catchments and moving windows it is beyond the scope of this paper to do a full uncertainty analysis as discussed in Marchant and Lark (2004). Therefore a stability test was carried out in order to verify if the changes detected in the TSV method are caused by a change in the autocorrelation structure or by a few extreme points influencing how the variogram model fits the data. This is usually undertaken by doing a split test. However, due to requirement of having a large data set to calculate the variogram, splitting the 5 year moving window in two was not deemed appropriate. Instead each data point in the 5 year moving window was randomly assigned to one of ten equal sized groups. The variogram was then fitted to the data 10 times, each time removing the data from one of the groups meaning that the variogram was fitted to 90% of the data. This resulted in 10 values for each variogram parameter which were calculated using 90% of the data. These points are then plotted against the variogram parameters which were calculated using 100% of the data to provide an indication as to the stability of the variogram parameter estimates.

3.4. Relating change to the meteorological drivers.

Having established patterns of temporal variability using the TSV approach, the potential meteorological drivers behind the detected changes in the variogram parameters are identified before being used to calculate how much of the change they explain.

Firstly, Pearson's product-moment correlation is calculated between the time-series of each of the four variogram parameters and the time-series of precipitation characteristics, calculated over the same time window. These results are used to determine the likely drivers behind each variogram parameter.

Secondly, Multiple Linear Regression (MLR) is undertaken in order to determine how much variance in the variogram parameters could be explained by a combination of different precipitation characteristics. As precipitation characteristics are correlated with each other, a procedure which penalises extra model parameters is required. Stepwise regression which tests whether parameters are significantly different from zero has limitations – in particular, it can lead to bias in the parameters, over-fitting and incorrect significance tests (see Whittingham et al. (2005) for an in depth discussion). In addition, the number and order of

the potential parameters can influence the final model (Burnham and Anderson, 2002). Instead, Information Theory (IT) based on Akaike's Information Criterion (AIC) is used to analyse how much information is added by each characteristic. For each catchment the model with the lowest AIC score is used to obtain the R^2 value which provides an indication into the amount of change in the variogram parameters which can be explained by precipitation.

The relative importance of each precipitation characteristic is also investigated,; providing information on which precipitation characteristics are important in explaining the changes in each variogram parameter. The relative importance is obtained by calculating the R^2 contribution averaged over orderings among regressors for each precipitation characteristic using the LMG method proposed by Linderman et al. (1980) (LMG), as recommended by Gromping (2006).

~~Autocorrelation is present in the variogram parameter time-series. Whilst this will not influence the amount of bias or consistency of the precipitation characteristics, positive autocorrelation will influence the efficiency of the explanatory variables and therefore overestimate the significance. However, analysing the residuals (using the Durbin-Watson test for autocorrelation disturbance) showed no significant autocorrelation. Therefore, regressing against several precipitation variables with similar autocorrelation to the variogram parameters (both averaged over five year moving windows) series adequately removes the autocorrelation.~~

Positive autocorrelation would influence the efficiency of the explanatory variables causing an overestimation of the significance. However, analysing the residuals from the MLR between precipitation and river flow (using the Durbin–Watson test for autocorrelation disturbance) showed no significant autocorrelation. Therefore, regressing against several precipitation variables with similar autocorrelation to the variogram parameters (both averaged over five year moving windows) is deemed to adequately remove the autocorrelation.

4. Testing the TSV method using artificially perturbed time-series

To demonstrate the suitability of the TSV approach, it was first applied to a river flow time-series with known artificially perturbed periods. To identify which variogram parameters

respond to changes in the river flow time-series, a series of artificial changes were imposed onto a seven year (1987 to 1994) section of the observed 32-year (1980 – 2012) de-seasonalised river flow time-series (Figure 3): five year moving windows starting between 1982 and 1994 (inclusive) will exhibit changes. The changes were imposed on three rivers, the South Tyne in the north-east of England, the Yscir in Wales and the Tove in eastern England. The three catchments range from a relatively upland catchment with low storage (South Tyne) to a more lowland catchment with higher storage (Tove), although still a catchment with limited groundwater contribution; Base-Flow Index (BFI) values are 0.45, 0.34 and 0.54 with drainage path slope (DPS) values of 138, 107 and 37 m km^{-1} for the Yscir, South Tyne and Tove, respectively (Marsh and Hannaford, 2008).

The perturbations applied represent plausible scenarios of the likely types of change to be seen in river flow time-series due to climate variability, other extrinsic drivers (e.g. land management) or a change in the gauging station.

- **Increase in the standard deviation:** a random, normally distributed set of numbers with a mean of zero and a standard deviation of 0.5 were added to the standardised river flow time-series.
- **Increase in variability:** the smallest 20 % of values were decreased by 20% whilst the largest 20% of values were increased by 20%.
- **Increased dependence:** a cosine wave with a wavelength of 365 days and amplitude of 0.5 was added to the standardised river flow time-series. This increases the relationship between river flow on successive days.
- **Increase in the mean:** 1.0 was added to all the standardised river flow time-series increasing the mean from 0 to 1.
- **Periods of persistence:** a 30 day period each December was forced to equal the mean.

Imposing artificial changes onto raw time-series was selected as a more challenging test for the variogram change detection method, compared to applying the changes to a randomly generated artificial statistically-stationary time-series, as it requires the method to be able to detect changes amongst the naturally occurring variability in the time-series. For all three catchments, a variogram was calculated for each five year overlapping moving window (i.e. 1980 – 1984, 1981 – 1985 ... 2008 – 2012) for the original and each of the artificial time-series (Figure 3). The variation in time of the variogram parameters provides information on whether the enforced changes in the input time-series would be detected, and on which ~~different~~ variogram parameters are affected by different types of change.

Figure 4 shows the outputs of the TSV analysis for the artificially modified time-series. The outputs from the three catchments were similar and therefore only the output from the South Tyne is shown, as an example.

The magnitude of change varies depending on the type of perturbation to the flow regime (Figure 4). Variogram parameters are sensitive to realistic changes to aspects of the flow regime which can cause the parameters to exceed the 5th or 95th percentile threshold. In addition, the individual variogram parameters respond differently to each of the changes:

Range: the only artificial perturbation which has a large influence on the Range is the dependence**.** The increase in Range is caused by creating dependency between flow on given days which lasts for a longer time.

Sill: influenced mainly by the dependence and variability. Adding a wave also increases the difference between the largest and smallest values, hence the total amount of variability (the Sill) increases.

HRASV: mainly influenced by the standard deviation and the variability, both of which influence the variability (short term and long term respectively). In addition the persistence also has a small negative impact as this would reduce the short term variability.

3 DASV: influenced by the same artificial perturbation as the HRASV, however, the variability has less of an influence.

5. Application of the TSV method to benchmark catchments
5.1. Stability analysis

Before the temporal changes are identifed, the stability of the variogram parameters was analysed to investigate if certain data points are having a large influence of the shape of the variogram and hence the variogram parameters. Figure 5 shows the relationship between the variogram parameters which are calculated using 100 % of the available river flow data and the same parameters calculated using 90 % of the available data. The figure highlights that there is a strong relationship between the points calculated using 90 and 100 % of the data. However, there are points which deviate much from the x=y gradient. The red dashed lines in Figure 5 represent small deviations from the y=x plot which are deemed to be an acceptable

amount of variation due to the removal of 10% of the data. Any catchment which has a point or more outside these lines, for any variogram parameter, was removed. This resulted in three catchments being removed from subsequent analysis. As well as the points outside of the red dashed lines, the Range has two groups of values that exceed the length of the red dashed lines (catchments with a Range of over 170 days). These two groups have large variability in the 10 values containing 90 % of the data. The large variability is probably due to the extrapolation by the model from the calculated semi-variance. Due to the fact that all the values are above the 95th threshold (and therefore it is likely that they capture a true change in the Range) these values were retained.

5.2. Identifying periods of change

Figure 65 identifies the periods when the TSV characteristics go above or below the 95th or 5th percentiles from the average variogram, respectively, for the 914 catchments. Different variogram parameters exhibit different changes through time. The 3 DASV shows relatively little change, until after 2004 when there is a peak in the number of catchments above the upper threshold. The Sill has peaks inof the number of catchments going above the upper threshold around 1980, 1990 and after 2004. The Range and the HRASV show several periods where the number of catchments above the upper threshold is much greater than the number of catchments below the lower threshold and vice versa. The Range and the HRASV see dramatic increases in the number of catchments which go beyond the lower and upper thresholds respectively, during approximately 1995 to 2001. Throughout this period the total amount of variability (the Sill) remains the same, as does the 3 DASV. The medium term variability (HRASV) shows an increase and the length of time the temporal dependence lasts (the Range) decreases. In addition to the 1995 to the 2001 period, every variogram parameter exhibits an increase in catchments exceeding the thresholds after around 2004. This indicates increases in the total (Sill) and short to medium term (3 DASV and HRASV) variability in the river flow time-series.

5.2.5.3.   Drivers behind the change

Initial analysis investigated the difference in precipitation between the periods which show the greatest changes, in terms of the number of catchments which go below / above the thresholds (approximately 1995 - 2001 and 2004 - 2012), with the preceding time-series (1980 – 1994). The periods where the most exceedances occur (1995 - 2001 and 2004 – 2012) are significantly more variable than the preceding time-series (Table 2).

To explore the links with drivers more quantitatively, the relationship between precipitation characteristics and variogram parameters in the 5-year moving windows were calculated, with the results summarised for all catchments in Table 3.

The Sill has the largest relationship with the winter to summer ratio (negative) followed by the standard deviation (positive). Although these appear contradictory, closer inspection found that the winter value seldom changed whereas the summer value increased (decreasing the winter to summer ratio), increasing the Sill. The Range is most correlated with the lower percentiles (negative) and the length of wet and dry periods (negative and positive respectively). Similar to the Sill, the 3 DASV has the largest correlations with the standard deviation (positive), winter to summer ratio (negative), mean (positive) and 90th percentile (positive). The largest correlations are with the HRASV which is highly correlated with the percentiles (positive), SD (positive) and the mean (positive).

Each variogram characteristic has a different relationship with the precipitation characteristics (Table 3). As expected from the artificial analysis (Figure 4) the Sill, HRASV and 3 DASV are more influenced by precipitation characteristics which affect the short term or total amount of variability in the time-series (e.g. standard deviation and the different percentiles). The Range is most influenced by aspects of the precipitation which enhance correlation between the river flow on successive days (e.g. length of wet and dry periods). The relationship between the precipitation characteristics and the Range is usually in the opposite direction to the other variogram parameters.

The average relative importance of each indicator in predicting each variogram parameter was calculated using the LMG method. The three most important characteristics for the Sill (accounting for over 30% of the explained variance between them) for the Sill are the winter to summer ratio, standard deviation and 90th percentile. The three most influential characteristics for the 3 DASV were the same as for the Sill. The average length of time

31

below and above 1 mm accounts for over 30% of the explained variance for the Range. For the HRASV, standard deviation, winter to summer ratio and the mean precipitation account for over 30% of the explained variance. Although these key drivers have been identified, the total amount of variability in the variogram parameters which is explained by precipitation characteristics is ~~varied~~ mixed and depends on both the variogram parameter and the catchment, as shown by the range of values of explained variance for individual catchments (Figure 7~~6~~).

6. Discussion

The TSV method provides information about temporal changes in the whole autocorrelation structure of the daily river flow data and shows the relationship between river flow on successive days. Persistent changes in precipitation can cause the river flow regime to change in a way which will alter the autocorrelation structure and be detectable using the TSV method. This is demonstrated by the ~~a~~Analysis of the artificially perturbed time-series which showed that it is possible to identify plausible and realistic (i.e. likely to be seen in a river flow time-series) changes in a river flow time-series using the Temporal Shifting Variogram (TSV) approach~~.~~, ~~to evaluate the temporally changing variogram parameters.~~ The TSV technique goes beyond monotonic change detection methods (such as the widely used Mann-Kendall test) as it does not require the whole time-series (which is driven by multiple non-linear interactions) to alter in a near-linear way for change to be detected. Change in any form (e.g. gradual linear and non-linear) can be characterised by plotting the variogram parameters over time. This is an advantage over change point analysis which is designed to detect abrupt changes. Another benefit of the TSV method is that it provides more information about the autocorrelation structure than an AR / ARMA model. Changes throughout different aspects of the river flow regime will be detected~~,~~ as the individual variogram parameters (Sill, Range, HRASV and 3 DASV) are sensitive to different types of change. Finally, the identified change is in relation to expected flow dynamics which represent the whole time period, enabling anomalous periods at the start and end of the records to be identified.

Applied to 91 UK catchments, the TSV method was able to identify clear changes from the normal river flow behaviour. Changes in each variogram parameter (Range, Sill, HRASV and

3 DASV) characterise different aspects of the river flow regime. The Range is dependent on the relationship between the flow on successive days; the value of the Sill depends on the overall variability; the 3 DASV is related to the day-to-day variability and the HRASV is a combination of short-term and long-term variability. As this is a new method, the changes in the variogram parameters are discussed below in the context of previous studies, on observed changes in river flow and precipitation, in order to corroborate the river flow variations that the variogram parameters are detecting, as well as their meteorological drivers.

The variogram parameters exhibit different changes throughout the record. For the Range there is as a clear increase in the number of catchments going below the lower threshold (5% threshold, from the 1,000 river flow time-series simulations) approximately between 1995 and 2001. Analysis of the perturbed time-series shows a decrease in the Range is likely to be caused by a reduction in the dependence between flow on successive days. This period was exceptionally wet (CEH, 2002) with less seasonality (Table 2) meaning that catchments would have often been wetter, decreasing the available storage and the lag time between precipitation and river flow and increasing the variability in river flow. This also indicates why the number of catchments which exceed the HRASV upper threshold (95% threshold) increases approximately between 1995 and 2001. The HRASV is influenced by standard deviation and variability in the river flow (Figure 4), both of which will be influenced by wetter conditions in the catchment.

Post-2004 there is a large increase in the number of catchments which exceed the upper threshold for the Sill. This increase is likely caused by the increase in variability of river flow after 2004 (Figure 4). This time period experienced some of the most unusual hydrological conditions in the UK since records began: among the highest annual precipitation totals on record were recorded in 2008 (CEH, 2009) whereas January to June 2010 was the second driest since 1910. The 2010 - 2012 drought, one of the most severe droughts for a century (Kendon et al., 2013) terminated abruptly, leading to widespread flooding due to the wettest April to July in England and Wales for almost 250 years (Parry et al., 2013). In addition, the standard deviation in the river flow was significantly larger than for both the 1980 – 1995 and the 1995 – 2001 periods. The high correlation between standard deviation and the 3 DASV explains the post-2004 increase in the number of catchments which exceed the upper threshold for the 3 DASV.

Different meteorological characteristics influence each variogram parameter. The Sill, HRASV and 3 DASV are largely controlled by precipitation characteristics which influence the total amount and variability of precipitation (mean, standard deviation, 95th percentile). The Range is more dependent on the length of wet and dry periods. The precipitation characteristics, on average, explain a large amount of the variability in the variogram parameters (Figure -76) (75%, 67%, 83% and 69% for the Sill, Range, HRASV and 3 DASV respectively). The medium term (half of the Range) variability has the strongest correlation with the precipitation characteristics (Table 3). This ~~is possibly because there is less of a relationship between precipitation and the 3 DASV and the Sill.~~suggests that the catchment characteristics may be having more of an influence on the relationship that the Sill and 3DASV have with precipitation.

Although, on average, precipitation explains a large proportion of the river flow variability, there are large differences in the amount of explained variability across catchments (Figure 76). The unexplained proportion could be caused by: (1) land management change or other human disturbances which would alter the precipitation-to-river flow relationship; (2) other meteorological characteristics not included in this paper; (3) catchment characteristics moderating how a river responds to temporal changes in precipitation; (4) unquantified error, (e.g. statistical error), including assumptions made when using information theory. With regards to the first of these factors, the analysis was carried out on benchmark catchments with limited abstractions / discharges; however, it is likely that other factors will have a greater role in catchments with less natural regimes. Benchmark catchments generally have relatively stable land cover but land use changes over time cannot be ruled out. Other meteorological characteristics (potential factor number 2) could be influential, for example, temperature which will influence the amount of snow and evapotranspiration. Snow will increase the lag time between precipitation and river flow. Furthermore if the snow melt is gradual this will act as a store of water, and the gradual release could influence the variogram, mimicking the effect of a groundwater aquifer. Snow can be important in runoff generation in upland areas of the UK, and in more low-lying settings in some winters. However, it is unlikely to make a large difference that would be discerned in the variogram of the majority of UK benchmark catchments. A change in the evapotranspiration losses over time could alter the magnitude of river flow, as well as seasonality. Assessing the role of additional meteorological characteristics is an important avenue of future work for developing the TSV methodology.

1 ~~but are more likely to be similar across catchments. In the third category, i~~It is well
2 documented that catchment characteristics moderate the precipitation-to-river flow
3 relationship (e.g. Sawicz et al. (2011) and Ley et al. (2011)) and, more specifically, have been
4 shown to exert a strong control over variogram properties (Chiverton et al. 2015). It therefore
5 stands to reason that the catchment characteristics could be enhancing or damping a rivers
6 response to changes in precipitation; influencing the non-linear precipitation to river flow
7 relationship. This would influence the amount of variability which can be explained by
8 multiple linear regression, and possibly explaining the wide range of degrees of explained
9 variance between catchments in Figure 7~~6~~. The influence of catchment characteristics could
10 explain why several studies (e.g. Hannaford and Buys (2012) and Pilon and Yue (2002)) find
11 regional inconsistencies in observed streamflow trends in catchments with broadly similar
12 meteorological characteristics. Therefore, the influence that catchment characteristics have on
13 moderating how a river responds to temporal changes in precipitation needs to be established.
14 Finally, using other methods to obtain the optimum combination of precipitation parameters
15 (other than IT and AIC) could produce different results.

16 Overall, the TSV approach has been shown to be a useful tool for characterising temporal
17 variability in river flow series, going beyond standard monotonic trend tests and relating the
18 changes to precipitation characteristics. As the method is able to detect non-linear changes,
19 and there are four variogram parameters which respond in different ways, a more detailed
20 analysis of links with drivers of change can be provided. In this study, this has been done
21 using a suite of meteorological indicators. However, the approach could also be used with
22 other explanatory variables (e.g. land use changes, changes in artificial influences, etc). In
23 this way, the method could find wider application as a tool for attribution of change using, for
24 example, the Multiple Working Hypothesis approach (e.g. Harrigan et al. (2014)).

25 **7. Conclusion**

26 This paper developed a new method of Temporally Shifting Variograms (TSV), for detecting
27 temporal changes in daily river flow. The TSV approach can detect periods of change
28 (increases and/or decreases) which result from linear or non-linear changes. Each variogram
29 parameter is related to a different aspect of the river flow, thus providing detailed information
30 as to how river flow dynamics have changed through time.

There are distinct time periods when there is a large increase in the number of UK benchmark catchments exceeding a threshold (around 1995 – 2001 for the Range and HRASV and post-2004 for all of the variogram parameters). The changes between 1995 and 2001 are attributed to an increase in precipitation; increasing the wetness of the catchment. Increased wetness reduced the amount of short term (< half the Range) variability which is removed by the catchment characteristics. The period after 2004 incorporated some of the most variable precipitation on record, influencing all of the variogram parameters. Meteorological factors explained a large proportion of the variability in the variogram parameters (75%, 67%, 83% and 69% for the Sill, Range HRASV and 3 DASV respectively). The amount of unexplained variability is potentially caused by catchment characteristics moderating how a river responds to temporal changes in atmospheric conditions.

This paper has demonstrated that TSV analysis enables changes in river flow dynamics to be characterised. The method will detect a wide range of changes (trends, variations in variability or standard deviation and step changes); the larger the magnitude of the change the less time is needed before the variogram parameters will exceed the thresholds. The principal advantages to the variograms are: the method is not influenced by the start and end points; changes near the start or the end of the record can be identified; non-linear changes can be detected; no indicators are needed and the four variogram parameters capture different aspects of the river flow dynamics. Variograms could also be used to identify the impact that catchment characteristics have on moderating how a river responds to temporal changes in precipitation, which could be valuable information for enabling detailed catchment management plans to be drawn up at a local level in a non-stationary environment.

8. References

Beaulieu, C., Chen, J., and Sarmiento, J. L.: Change-point analysis as a tool to detect abrupt climate variations, 1962, 1228-1249 pp., 2012.

Bradford, R., and Marsh, T.: Defining a network of benchmark catchments for the UK, Water and Maritime Engineering, 156, 109-116, 2003.

Burn, D. H., Hannaford, J., Hodgkins, G. A., Whitfield, P. H., Thorne, R., and Marsh, T.: Reference hydrologic networks II. Using reference hydrologic networks to assess climate-driven changes in streamflow, Hydrological Sciences Journal, 57, 1580-1593, 10.1080/02626667.2012.728705, 2012.

Burnham, K., P. , and Anderson, D., R.: Model selection and multimodel inference: a practice ractical informatic-theoretic approach, Springer Verlag, New York, 2002.

CEH: Hydrological Review of 2001, Centre for Ecology and Hydrology, Oxfordshire, UK, 2002.

CEH: UK Hydrological Review 2008, Centre for Ecology & Hydrology, Oxfordshire, UK, 2009.

Chandler, R., and Scott, M.: Statistical Methods for Trend Detection and Analysis in the Environmental Sciences, John Wiley and Sons, Ltd, Chichester, West Sussex, 367 pp., 2011.

Chen, Z., and Grasby, S. E.: Impact of decadal and century-scale oscillations on hydroclimate trend analyses, Journal of Hydrology, 365, 122-133, http://dx.doi.org/10.1016/j.jhydrol.2008.11.031, 2009.

Chiverton, A., Hannaford, J., Holman, I., Corstanje, R., Prudhomme, C., Bloomfield, J., and Hess, T. M.: Which catchment characteristics control the temporal dependence structure of daily river flows?, Hydrological Processes, 29, 1353-1369, 10.1002/hyp.10252, 2015.

Chun, K. P., Wheater, H., and Onof, C.: Prediction of the impact of climate change on drought: an evaluation of six UK catchments using two stochastic approaches, Hydrological Processes, 27, 1600-1614, 10.1002/hyp.9259, 2013.

Cressie, N., A, C.: When Are Relative Variograms Useful in Geostatistics?, Mathematical Geology, 17, 563-586, 1985.

Gosling, S., and Arnell, N.: A global assessment of the impact of climate change on water scarcity, Climatic Change, 1-15, 10.1007/s10584-013-0853-x, 2013.

Gromping, U.: Relative importance for linear regression in R: The package relaimpo, J Stat Softw, 17, 2006.

Hall, J., Arheimer, B., Borga, M., Brázdil, R., Claps, P., Kiss, A., Kjeldsen, T. R., Kriaučiūnienė, J., Kundzewicz, Z. W., Lang, M., Llasat, M. C., Macdonald, N., McIntyre, N., Mediero, L., Merz, B., Merz, R., Molnar, P., Montanari, A., Neuhold, C., Parajka, J., Perdigão, R. A. P., Plavcová, L., Rogger, M., Salinas, J. L., Sauquet, E., Schär, C., Szolgay, J., Viglione, A., and Blöschl, G.: Understanding flood regime changes in Europe: a state of the art assessment, Hydrol. Earth Syst. Sci. Discuss., 10, 15525-15624, 10.5194/hessd-10-15525-2013, 2013.

Hannaford, J., and Buys, G.: Trends in seasonal river flow regimes in the UK, Journal of Hydrology, 475, 158-174, http://dx.doi.org/10.1016/j.jhydrol.2012.09.044, 2012.

Hannaford, J., Buys, G., Stahl, K., and Tallaksen, L. M.: The influence of decadal-scale variability on trends in long European streamflow records, Hydrol. Earth Syst. Sci., 17, 2717-2733, 10.5194/hess-17-2717-2013, 2013.

Harrigan, S., Murphy, C., Hall, J., Wilby, R. L., and Sweeney, J.: Attribution of detected changes in streamflow using multiple working hypotheses, Hydrol. Earth Syst. Sci., 18, 1935-1952, 10.5194/hess-18-1935-2014, 2014.

Havard, R., and Held, L.: Gaussian Markov Random Fields: Theory and Applications, 1 ed., Chapman & Hall/CRC, London, UK, 280 pp., 2005.

Hipel, K. W., and McLeod, A. I.: Time Series Modelling of Water Resources and Environmental Systems, Electronic reprint of the book orginally published in 1994., 2005.

Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., Kim, H., and Kanae, S.: Global flood risk under climate change, Nature Clim. Change, 3, 816-821, 10.1038/nclimate1911 http://www.nature.com/nclimate/journal/v3/n9/abs/nclimate1911.html#supplementary-information, 2013.

Holman, I., Rivas-Casado, M., Bloomfield, J., and Gurdak, J.: Identifying non-stationary groundwater level response to North Atlantic ocean-atmosphere teleconnection patterns using wavelet coherence, Hydrogeol J, 19, 1269-1278, 10.1007/s10040-011-0755-9, 2011.

Hughes, D., A., and Smakhtin, V.: Daily flow time series patching of extension: a spatial interpolation approach based on flow duration curves Hydrological Sciences Journal, 41, 851 - 871, 1996.

Huntington, T. G.: Evidence for intensification of the global water cycle: Review and synthesis, Journal of Hydrology, 319, 83-95, http://dx.doi.org/10.1016/j.jhydrol.2005.07.003, 2006.

IPCC: Climate change 2013: The Physical Science Basis. Contribution of Working group l., Cambridge University Press, New York, 2013.

Jandhyala, V., Fotopoulos, S., MacNeill, I., and Liu, P.: Inference for single and multiple change-points in time series, Journal of Time Series Analysis, n/a-n/a, 10.1111/jtsa12035, 2013.

Jarušková, D.: Some Problems with Application of Change-Point Detection Methods to Environmental Data, Environmetrics, 8, 469-483, 10.1002/(SICI)1099-095X(199709/10)8:5<469::AID-ENV265>3.0.CO;2-J, 1997.

Journel, A., G., and Huijbregts, C., J.: Mining Geostatistics, Academic Press, New York, 1978.

Keller, V. D. J., Tanguy, M., Prosdocimi, I., Terry, J. A., Hitt, O., Cole, S. J., Fry, M., Morris, D. G., and Dixon, H.: CEH-GEAR: 1 km resolution daily and monthly areal rainfall estimates for the UK for hydrological use, Earth Syst. Sci. Data Discuss., 8, 83-112, 10.5194/essdd-8-83-2015, 2015.

Kendon, M., Marsh, T., and Parry, S.: The 2010–2012 drought in England and Wales, Weather, 68, 88-95, 10.1002/wea.2101, 2013.

Kjeldsen, T. R., Macdonald, N., Lang, M., Mediero, L., Albuquerque, T., Bogdanowicz, E., Brázdil, R., Castellarin, A., David, V., Fleig, A., Gül, G. O., Kriauciuniene, J., Kohnová, S., Merz, B., Nicholson, O., Roald, L. A., Salinas, J. L., Sarauskiene, D., Šraj, M., Strupczewski, W., Szolgay, J., Toumazis, A., Vanneuville, W., Veijalainen, N., and Wilson, D.: Documentary evidence of past floods in Europe and their utility in flood frequency estimation, Journal of Hydrology, 517, 963-973, http://dx.doi.org/10.1016/j.jhydrol.2014.06.038, 2014.

Kumar, M., and Duffy, C. J.: Detecting hydroclimatic change using spatio-temporal analysis of time series in Colorado River Basin, Journal of Hydrology, 374, 1-15, http://dx.doi.org/10.1016/j.jhydrol.2009.03.039, 2009.

Labat, D.: Recent advances in wavelet analyses: Part 1. A review of concepts, Journal of Hydrology, 314, 275-288, http://dx.doi.org/10.1016/j.jhydrol.2005.04.003, 2005.

Ley, R., Casper, M. C., Hellebrand, H., and Merz, R.: Catchment classification by runoff behaviour with self-organizing maps (SOM), Hydrol. Earth Syst. Sci., 15, 2947-2962, 10.5194/hess-15-2947-2011, 2011.

Linderman, R., H., Merenda, P., F., and Gold, R., Z.: Introduction to Bivariate and Multivariate Analysis, Longman, Harlow, UK, 1980.

Marchant, B. P., and Lark, R. M.: Estimating Variogram Uncertainty, Mathematical Geology, 36, 867-898, 10.1023/B:MATG.0000048797.08986.a7, 2004.

Marsh, T., and Hannaford, J.: K Hydrometric Register. , Hydrological data UK series. , Centre for Ecology & Hydrology, Wallingford, UK, 2008.

Merz, B., Vorogushyn, S., Uhlemann, S., Delgado, J., and Hundecha, Y.: HESS Opinions "More efforts and scientific rigour are needed to attribute trends in flood time series", Hydrol. Earth Syst. Sci., 16, 1379-1387, 10.5194/hess-16-1379-2012, 2012.

Montanari, A., Rosso, R., and Taqqu, M. S.: Fractionally differenced ARIMA models applied to hydrologic time series: Identification, estimation, and simulation, Water Resources Research, 33, 1035-1044, 10.1029/97WR00043, 1997.

Montanari, A., Young, G., Savenije, H. H. G., Hughes, D., Wagener, T., Ren, L. L., Koutsoyiannis, D., Cudennec, C., Toth, E., Grimaldi, S., Blöschl, G., Sivapalan, M., Beven, K., Gupta, H., Hipsey, M., Schaefli, B., Arheimer, B., Boegh, E., Schymanski, S. J., Di Baldassarre, G., Yu, B., Hubert, P., Huang, Y., Schumann, A., Post, D. A., Srinivasan, V., Harman, C., Thompson, S., Rogger, M., Viglione, A., McMillan, H., Characklis, G., Pang, Z., and Belyaev, V.: "Panta Rhei—Everything Flows": Change in hydrology and society—The IAHS Scientific Decade 2013–2022, Hydrological Sciences Journal, 58, 1256-1275, 10.1080/02626667.2013.809088, 2013.

Pagano, T., and Garen, D.: A Recent Increase in Western U.S. Streamflow Variability and Persistence, Journal of Hydrometeorology, 6, 173-179, 10.1175/JHM410.1, 2005.

Parry, S., Marsh, T., and Kendon, M.: 2012: from drought to floods in England and Wales, Weather, 68, 268-274, 10.1002/wea.2152, 2013.

Pilon, P. J., and Yue, S.: Detecting climate-related trends in streamflow data, Water science and technology : a journal of the International Association on Water Pollution Research, 45, 89-104, 2002.

Prudhomme, C., Jakob, D., and Svensson, C.: Uncertainty and climate change impact on the flood regime of small UK catchments, Journal of Hydrology, 277, 1-23, http://dx.doi.org/10.1016/S0022-1694(03)00065-9, 2003.

Rougé, C., Ge, Y., and Cai, X.: Detecting gradual and abrupt changes in hydrological records, Advances in Water Resources, 53, 33-44, http://dx.doi.org/10.1016/j.advwatres.2012.09.008, 2013.

Salas, J. D., Boes, D. C., and Smith, R. A.: Estimation of ARMA Models with seasonal parameters, Water Resources Research, 18, 1006-1010, 10.1029/WR018i004p01006, 1982.

Sang, Y.-F.: A review on the applications of wavelet transform in hydrology time series analysis, Atmospheric Research, 122, 8-15, http://dx.doi.org/10.1016/j.atmosres.2012.11.003, 2013.

Sawicz, K., Wagener, T., Sivapalan, M., Troch, P. A., and Carrillo, G.: Catchment classification: empirical analysis of hydrologic similarity based on catchment function in the eastern USA, Hydrol. Earth Syst. Sci., 15, 2895-2911, 10.5194/hess-15-2895-2011, 2011.

Sen, A. K.: Spectral-temporal characterization of riverflow variability in England and Wales for the period 1865–2002, Hydrological Processes, 23, 1147-1157, 10.1002/hyp.7224, 2009.

Smith, L. C., Turcotte, D. L., and Isacks, B. L.: Stream flow characterization and feature detection using a discrete wavelet transform, Hydrological Processes, 12, 233-249, 10.1002/(SICI)1099-1085(199802)12:2<233::AID-HYP573>3.0.CO;2-3, 1998.

Tanguy, M., Dixon, H., Prosdocimi, I., Morris, D. G., and Keller, V. D. J.: Gridded estimates of daily and monthly areal rainfall for the United Kingdom (1890-2012) [CEH-GEAR], NERC Environmental Information Data Centre, http://dx.doi.org/10.5285/5dc179dc-f692-49ba-9326-a6893a503f6e, 2014.

Watts, G., Battarbee, R., Bloomfield, J., P., Crossman, J., Daccache, A., Durance, I., Elliot, J., Garner, G., Hannaford, J., Hannah, D., M., Hess, T., Jackson, S., R., Kay, A., L., Kernan, M., Knox, J., Mackay, J., Monteith, D., T., Ormerod, S., Rance, J., Stuart, M., E., Wade, A., J., Wade, S., D., Weatherhead, K., Whitehead, P., G., and Wilby, R., L.: Climate change and water in the UK – past changes and future prospects., Progress in Physical Geography, in press.

Webster, R., and Oliver, M.: Geostatistics for Environmental Scientists, John Wiley and Sons, Ltd, Chichester, West Sussex, 315 pp., 2007.

Whittingham, M. J., Swetnam, R. D., Wilson, J. D., Chamberlain, D. E., and Freckleton, R. P.: Habitat selection by yellowhammers Emberiza citrinella on lowland farmland at two spatial scales: implications for conservation management, Journal of Applied Ecology, 42, 270-280, 10.1111/j.1365-2664.2005.01007.x, 2005.

Yue, S., Kundzewicz, Z. W., and Wang, L.: Detection of changes, in: Changes in Flood Risk in Europe, IAHS Press, Wallingford, UK, 2012.

1

2

3

4

5

Figure 1   Locations of the catchments used in this paper.
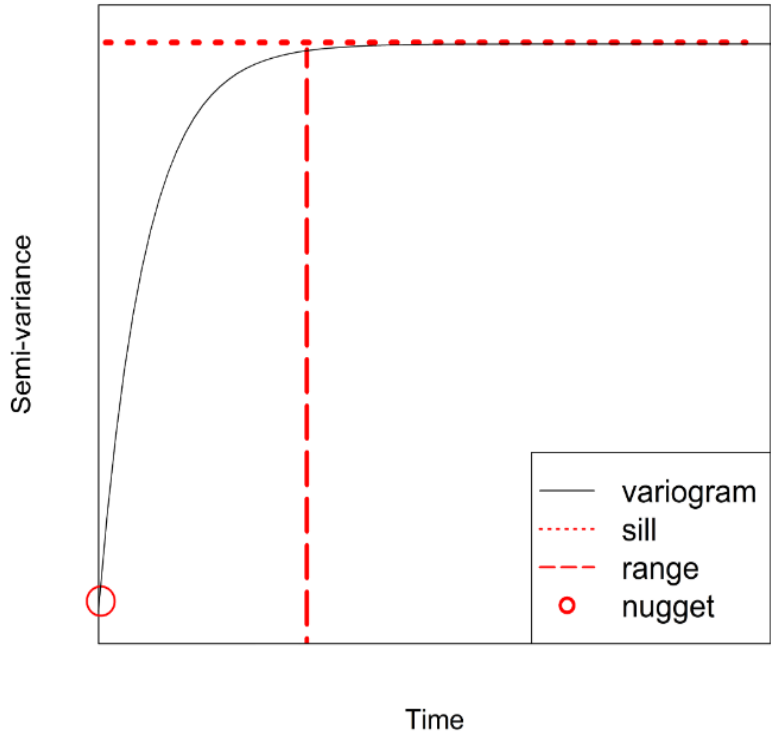
Figure 2   Theoretical variogram.
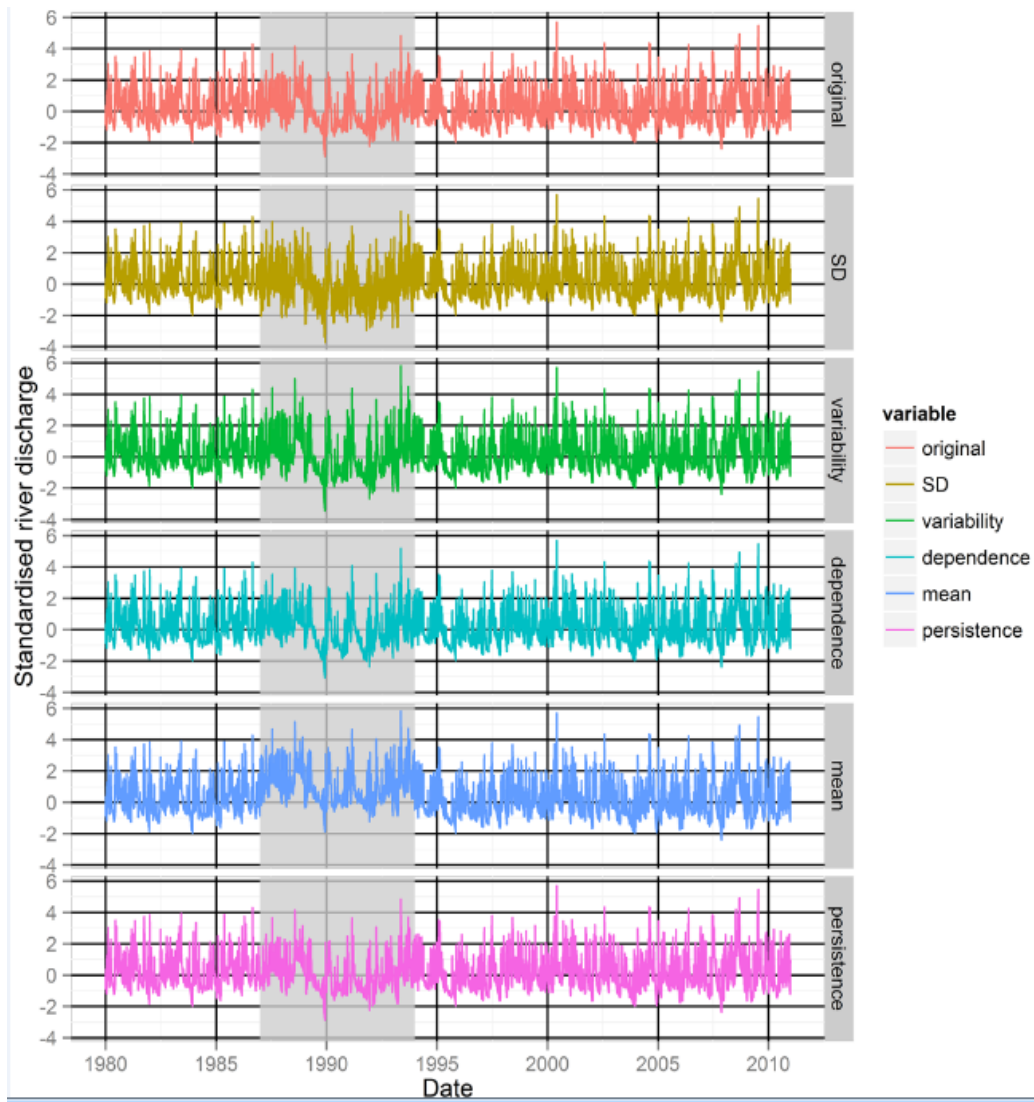
Figure 3   The time-series resulting from the addition of artificial changes between 1987
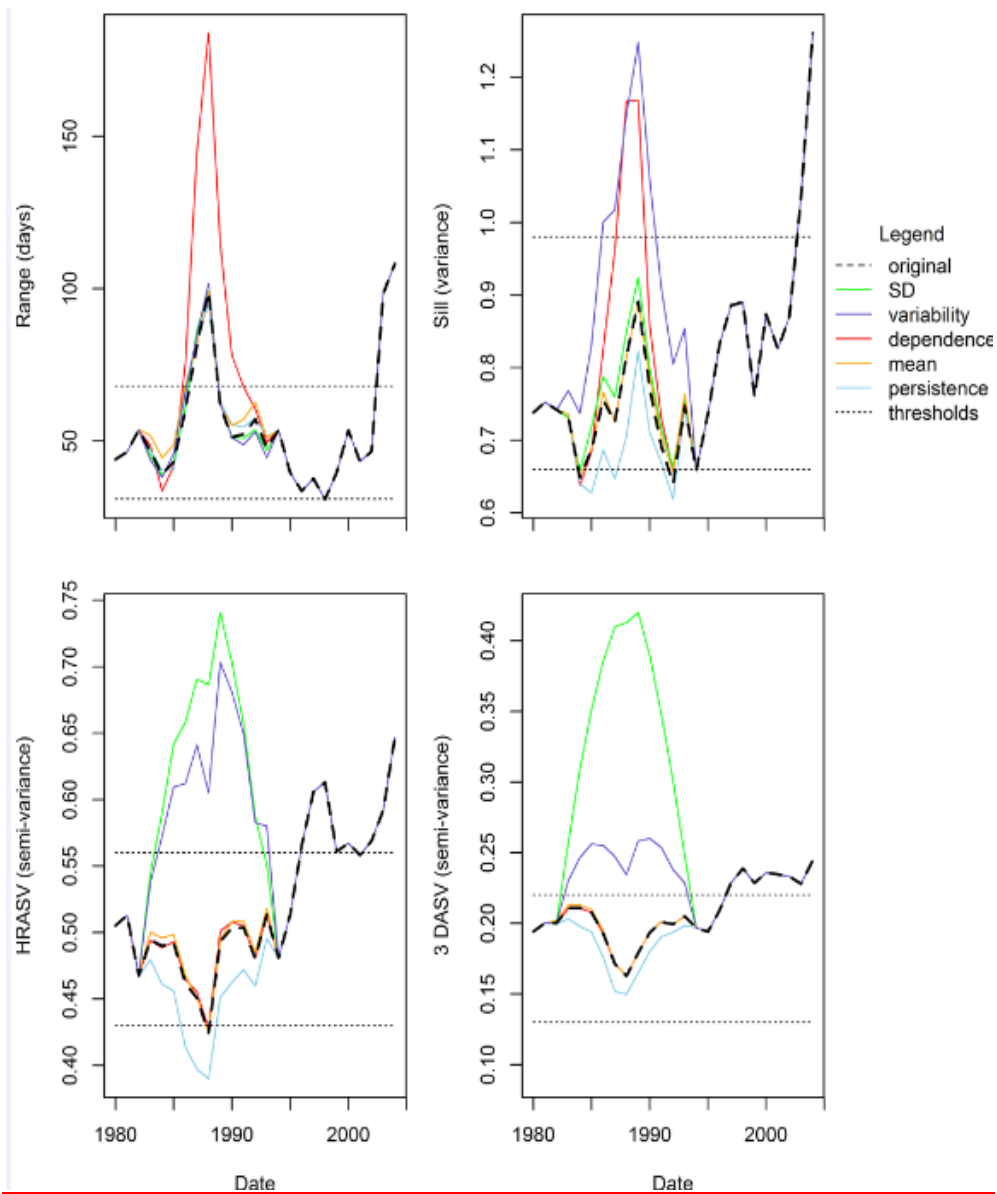   and 1994 (shaded area) to normalised river flows for the South Tyne river.

Figure 4   Changes in the variogram parameters resulting from the artificial changes to the time-series for the South Tyne
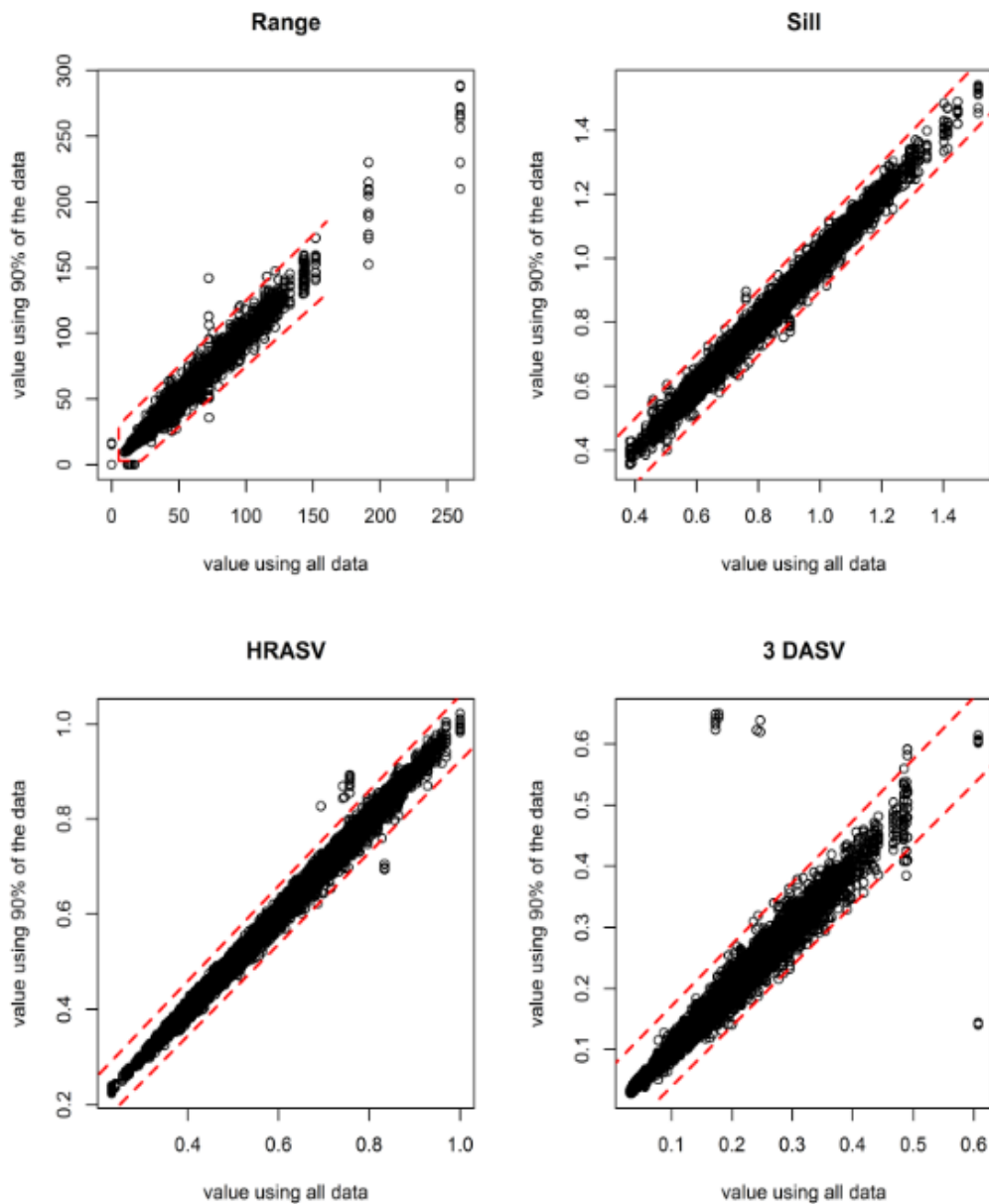
Figure 5   Relationship between the variogram parameters when calculated using all the available data and the parameters using 90 % of the data. The red lines show the range of acceptable values. Any catchments with points outside the red lines were removed.
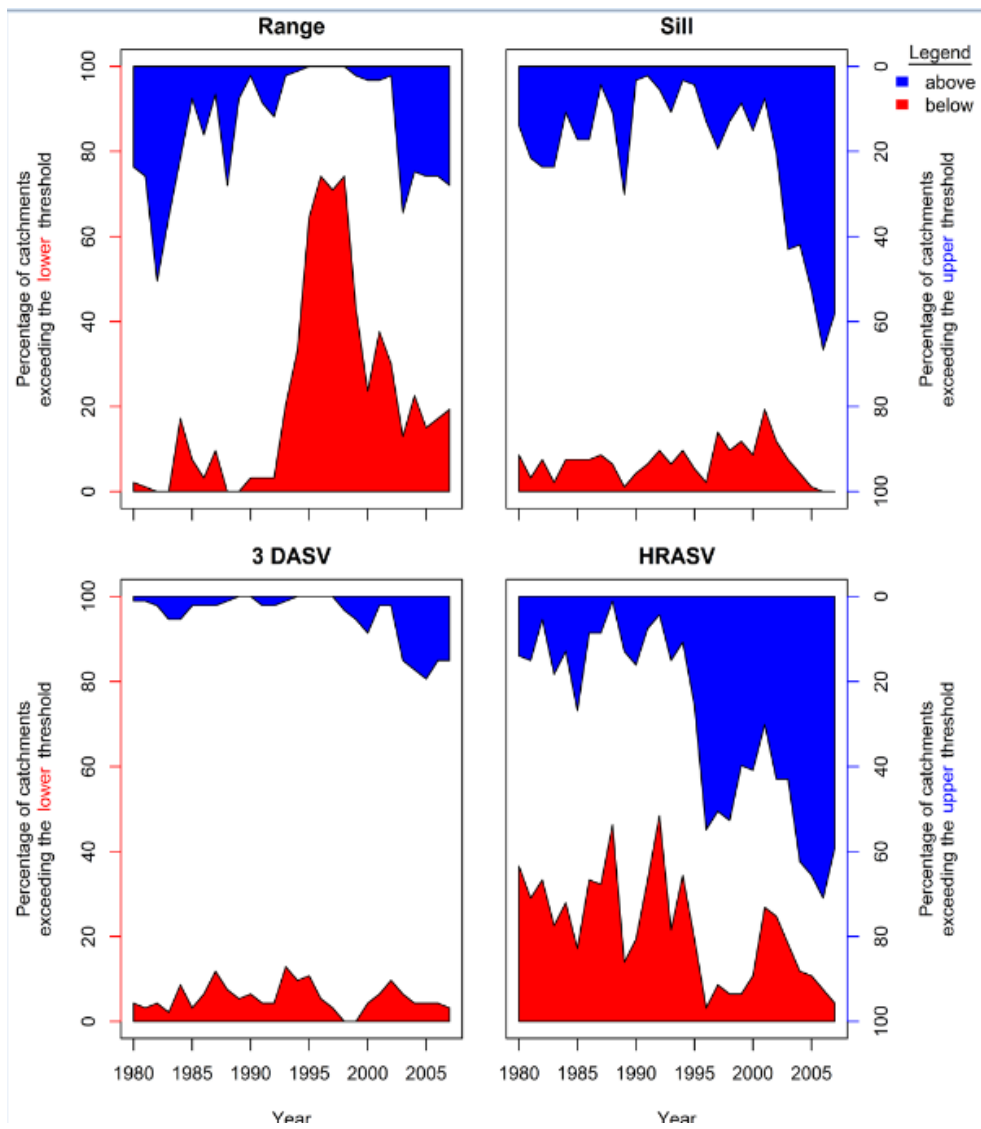
Figure 65 Percentage of catchments which exceed thresholds through time.
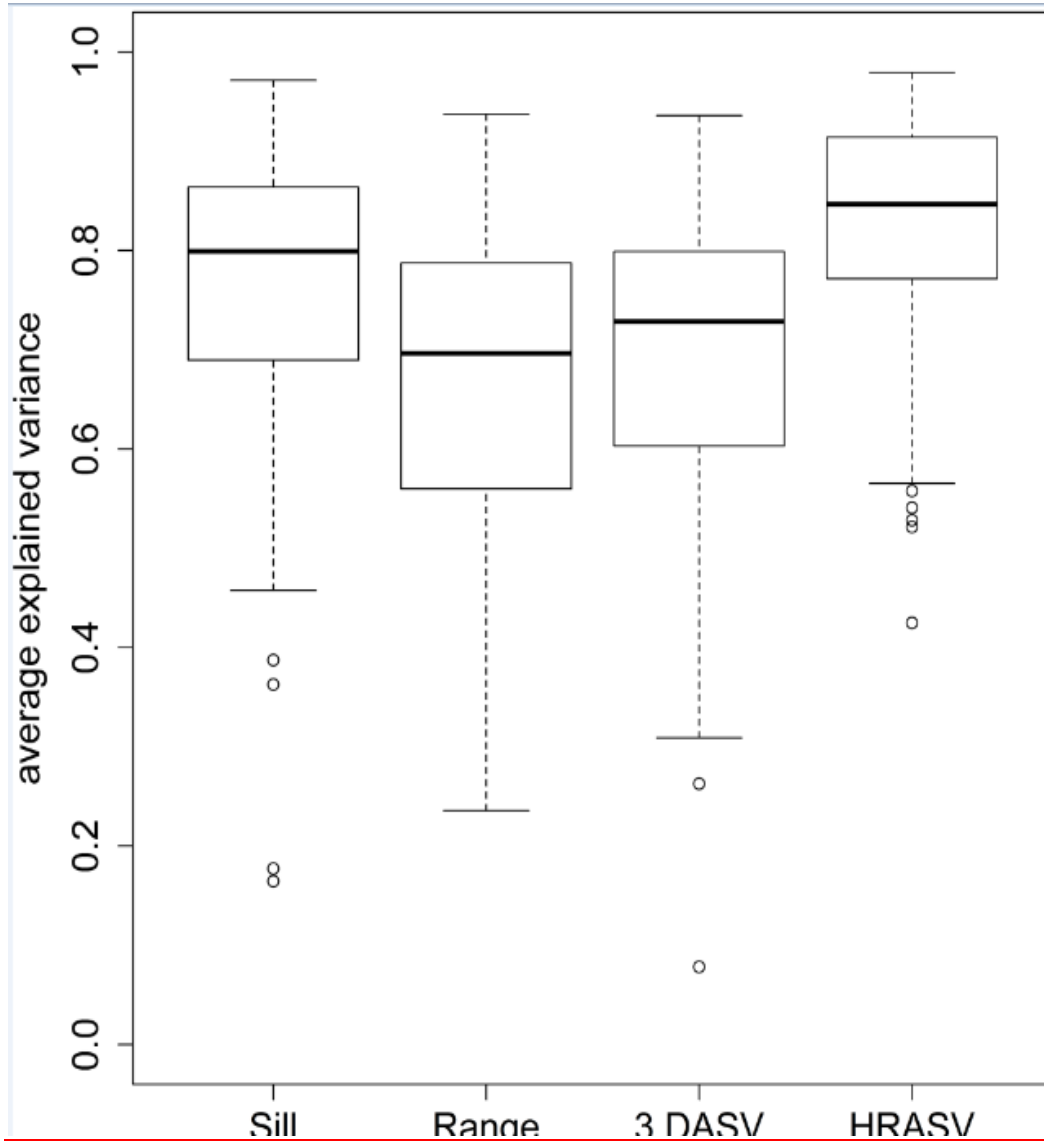
Figure 76   Box and whisker plot of the average variance in 5 year variogram characteristics explained by meteorological characteristics, calculated using the adjusted R^2 value and the variables in the model with the lowest AIC value (calculated using IT) for each catchment.

Table 1: Daily precipitation characteristics.

Precipitation characteristic	Units	Description
Mean	mm	Average daily precipitation values
Standard deviation	mm	Standard deviation of the daily precipitation values
25th percentile	mm	Daily precipitation amount which is not exceeded 25% of the time
Median	mm	Daily precipitation amount which is not exceeded 50% of the time
75th percentile	mm	Daily precipitation amount which is not exceeded 75% of the time
90th percentile	mm	Daily precipitation amount which is not exceeded 90% of the time
95th percentile	mm	Daily precipitation amount which not is exceeded 95% of the time
Max length of precipitation above or below 1mm day^{-1}	days	The maximum number of successive days for which the precipitation is above/below the threshold.
Average length of precipitation above or below 1mm day^{-1}	days	The average number of successive days for which the precipitation is above/below the threshold. Only periods of time greater than 2 days were analysed.
Winter / summer precipitation ratio	unitless	The mean rainfall in December, January and February divided by the mean rainfall for June, July and August.
Autumn / spring precipitation ratio	unitless	The mean rainfall in September, October and November divided by the mean rainfall for March, April and May.

Table 2: Change in the median value of the potential driving characteristics for 1995 – 2001 and 2004 - 2012, compared to 1980 – 1994. The median value (taken from all the 914 catchments) is presented along with the significance level (if significantly different from 1980 – 1994 at or above the 95% CI).

Characteristic	1980 - 1994	1995 - 2001	2004 - 2012
Mean (standardised)	-0.013	-0.006 (99.9%)	0.006 (99.9%)
Standard deviation (standardised)	0.975	0.993 (99%)	1.01 (99.9%)
Median (standardised)	-0.461	-0.458 (95%)	-0.451(99.9%)
25th percentile (standardised)	-0.55	-0.55	-0.55
75th percentile (standardised)	0.10	0.12 (99%)	0.14 (99.9%)
90th percentile (standardised)	1.12	1.16 (99.9%)	1.17 (99.9%)
Winter / Summer	1.36	1.60 (99.9%)	1.03 (99.9%)
Autumn / Spring	1.32	1.48 (99.9%)	1.47 (99.9%)
Max consecutive number of days below 1 mm (days)	29	27 (99%)	25 (99.9%)
Max consecutive number of days above 1 mm (days)	16	17	16
Average consecutive number of days below 1 mm (days)	17	17	17
Average consecutive number of days above 1 mm (days)	16	16	16

Table 3: Percentage of catchments with significant (at the 95% CL) correlation between the 5 year precipitation and variogram characteristics. The average correlation (for catchments with significant correlations) is in brackets. The darker the colour, the larger the average absolute correlation.

Characteristic	Range	Sill	HRASV	3 DASV
Mean	30 (-0.42)	37 (0.33)	54 (0.62)	32 (0.47)
Standard deviation	35 (-0.31)	48 (0.47)	64 (0.62)	43 (0.53)
Average length of wet period (above 1mm)	55 (-0.47)	54 (-0.09)	63 (0.12)	48 (-0.20)
Average length of dry period (below 1mm)	52 (0.49)	48 (-0.11)	58 (-0.11)	39 (-0.12)
Max length of wet period (above 1mm)	34 (-0.21)	32 (-0.04)	27 (0.08)	31 (-0.05)
Max length of dry period (below 1mm)	38 (0.50)	32 (0.24)	35 (-0.21)	30 (-0.02)
25th percentile	31 (-0.50)	32 (0.12)	43 (0.53)	27 (0.36)
Median	42 (-0.43)	32 (0.06)	53 (0.48)	25 (0.37)
75th percentile	34 (-0.21)	31 (0.11)	56 (0.51)	27 (0.38)
90th percentile	30 (-0.12)	38 (0.34)	51 (0.52)	34 (0.42)
Winter / Summer	24 (-0.36)	65 (-0.51)	60 (-0.51)	56 (-0.44)
Autumn / Spring	15 (-0.19)	23 (0.01)	26 (0.16)	20 (-0.02)