LONG-RUN PERSISTENCE IN RESERVOIR INFLOWS: EMPIRICAL MODE DECOMPOSITION IN SYDNEY AND MELBOURNE

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ABSTRACT

This paper quantifies long-run hydrological persistence in reservoir inflows to two regions: Melbourne and Sydney. We use a relatively new approach in hydrology, Empirical Mode Decomposition (EMD). Our three key results are summarised below:

(1) For Melbourne and Sydney inflows, 57-66% of total variance was accounted for by periodicities <10 years; 20-21% of total variance was attributable to periodicities >10 years; and 14-22% of variance is residual.

(2) Long-run persistence is cross-correlated between key reservoir inflows within each region.

(3) Coincidence of troughs in multiple Intrinsic Mode Functions (IMFs) may be associated with intense drought periods (and vice versa), and may further be associated with hydro-meteorological influences. We examined one such influence (Southern Oscillation Index, [SOI]) and found significant correlations in Sydney.

The relatively high proportion of inflow variance represented by long-run (>10 years) components is a strong illustrator of long-run hydrological persistence in these two regions. If not accounted for by water supply planners, long-run hydrological persistence may contribute to larger water supply reliability risk. Further, the regional cross-correlation of long-run persistence may amplify this risk, where there is high reliance on climate-dependent sources (e.g. reservoir inflows) for a city's water supply.

EMD represents a potentially powerful approach for water supply planners seeking to improve reliability estimates through explicit incorporation of long-run hydrological persistence into future inflow modelling. This paper also presents a number of methodological insights that are helpful for water resource practitioners seeking to apply this accessible method.

INTRODUCTION

Long-run hydrological persistence is pervasive in historical river flow data. The implications of persistence are especially salient for major cities striving to achieve cost-effective reliability in their future water supply strategies, particularly in regions where hydrology is strongly influenced by major climatic systems such as the El Niño Southern Oscillation (ENSO). Cities on both sides of the Pacific (East Coast Australia and West Coast United States) have recently experienced the downside of hydrological persistence in the form of record droughts that have prompted diversification of water supply portfolios, including alternative climate-independent sources such as desalination. Furthermore, interactions between persistence and climate change are just starting to be explored, and the latter may further amplify persistence.

Explicit incorporation of long-run hydrological persistence has not to date always featured in water supply planning by agencies. Persistence may pose a downside risk to reliability: hence reliability estimates excluding persistence effects may be overstated. One potential obstacle for water supply agencies is the accessibility of appropriate techniques to explicitly incorporate hydrological persistence in their reliability modelling. Some analysts have also questioned the reliability improvement to be expected, reasoning that it may not be worth the additional effort (Klemes et al. 1981).

This paper applies a novel, accessible method to capture persistence: EMD. Originally developed in oceanography, this paper is amongst the first to apply the method directly to reservoir inflows.

PROJECT CONTEXT

Results presented in this paper constitute Phase 1 of a multi-year project titled 'Insuring the Reliability of a City's Water Supply', led by the University of Melbourne with collaborative partners including Melbourne Water Corporation and Water NSW.[1] The hydrological component of the project involves applied time series analysis and modelling of historical natural inflows supporting two of Australia's largest cities: Sydney and Melbourne.

The EMD results presented in this paper are a critical input to Phase 2 of the project, which will prepare leading practice inflow models for the respective cities. The aim is to synthetically generate multiple reservoir inflows which replicate the features of the original series. This includes both observed short-run effects (cross-correlation and autocorrelation); and explicit capture of long-

[1] Prior to 01 Jan 2015, this agency was Sydney Catchment Authority.

run hydrological persistence. These future inflow models are designed for use by water supply agencies for scenario modelling to evaluate their city's water portfolio options and make sound investment decisions to secure their future water reliability.

STUDY REGIONS

This paper examines reservoir inflows supplying two cities: Melbourne and Sydney. Historical natural inflow data (consisting of measurement records with modelled reconstructions of incomplete and missing data) were provided by the lead water agencies in each city responsible for managing the respective reservoir networks, and the supply of water from these to the cities. Data were available for four reservoirs managed by Melbourne Water Corporation (Thomson, Upper Yarra, O'Shannassy and Maroondah) for a 98-year period (1913-2010). For Sydney, data were available for nine reservoirs managed by Water NSW (Warragamba, Nepean, Cataract, Avon, Cordeaux, Woronora, Wingecarribee, Fitzroy Falls and Tallowa) for a 104-year period (1909-2012). Basic descriptive statistics for these inflow series are presented in Table 1.

This paper considers only the historical natural inflow series: it does not encompass any reservoir storage or operational factors. EMD was applied to total annual inflows, based on the calendar year.

Table 1: Inflow statistics. SD= Standard Deviation; CV=Coefficient of Variation

Inflow:		$\bar{x}$ [GL pa]:	SD [GL pa]:	CV:
Melbourne n=98 [1913-2010]	Thom	245.08	83.09	0.339
	UY	153.79	66.81	0.434
	OShan	100.37	30.43	0.303
	Maroon	83.54	25.04	0.300
		$\bar{x}$:		**0.344**
Sydney n=104 [1909-2012]	Warra	1,058.59	1,145.70	1.082
	Nep	101.21	98.02	0.968
	Cat	81.11	52.21	0.644
	Avon	69.17	55.70	0.805
	Cord	53.87	37.45	0.695
	Woro	40.63	31.60	0.778
	Wing	13.78	8.49	0.616
	Fitz	12.05	6.19	0.514
	Tall	1,201.19	1,176.10	0.979
		$\bar{x}$:		**0.787**

LITERATURE REVIEW

Approaches to Characterising Long-Run Persistence

Quantifying long-run persistence in hydrological time series is best-informed by plausible hypotheses regarding causal mechanisms. Natural reservoir inflows are generally understood to result from multiple hydro-meteorological influences (Data Generating Processes [DGPs]) occurring over various time horizons. Prominent regional influences include ENSO (periodicities ranging over 3-7 years) and the Interdecadal Pacific Oscillation (IPO: 10-25 years). Our basic premise is that superimposition of these DGPs introduces hydrological persistence over a range of scales.

This renders the task of quantifying long-run persistence as one of *decomposing* a hydrological time series into discrete signals operating over a range of time-frequency domains, with each signal potentially representing a discrete hydro-meteorological influence. These signals may be comprised of periodic, monotonic and random components.

In the past, characterization of the DGPs that influence hydrological persistence has been attempted using a range of methods. Generic techniques for signal decomposition date from Fourier (1822) and gave rise to the modern discipline of Singular Spectral Analysis (SSA). The Hurst exponent (Hurst 1951) is an early and simple quantitative measure of long-term hydrological 'memory', based on British water engineer Hurst's pioneering work on historical river flow records on the Nile. The Hurst exponent has been used in multiple hydrologic analyses.

Wavelet analysis represents a more recent method that has found application in hydrology. However, all of these techniques have limitations, prominent amongst them being assumptions of stationarity. EMD is an alternative method for identifying signals operating over a range of time-frequency domains, and its advantage over traditional decomposition approaches is its ability to identify **non-stationary** modes of persistence with varying frequency and amplitude over time (Huang et al. 1998). The EMD approach has been successfully applied to global precipitation records (Pegram et al. 2008; Peel et al. 2009); and McMahon et al. (2008) have applied it to local (Canberra) rainfall records. EMD is beginning to be applied to hydrological records internationally (Napolitano et al. 2011; Sang et al. 2012; and Karthikeyan and Kumar 2013), though has yet to be extensively applied to hydrological records in Australia.

METHODS

EMD is used to decompose an original series into a set of IMFs (Huang et al. 1998). Each IMF has a characteristic periodicity, and by construction is theoretically independent (orthogonal) to the other IMFs in the set. The systematic decomposition into IMFs is conducted in a series of steps:

1) identify the local maxima and minima (collectively: extrema) of the original series;

2) fit a spline to the maxima to create an upper envelope;

3) fit a spline to the minima to create a lower envelope;
4) calculate the local mean of the two envelopes and subtract this from the candidate series; and
5) check the newly created series against the IMF conditions.

IMFs must satisfy two conditions (Huang et al. 1998):

a. the number of zero crossings for the candidate series must be within +/- 1 of the total number of extrema. (This ensures the dataset is discrete, complete, and sampled at consistent time intervals); and
b. the mean of the envelope defined by the local minima and maxima is zero

If the IMF conditions are not met, steps 1-5 are repeated iteratively in a process called sifting (Huang et al. 1998). Sifting has two objectives: to eliminate riding waves and to increase the symmetry of the wave profile in the series (Huang et al. 1998). A 'stopping criterion' for sifting is defined by the user. We have adopted the criterion of Huang et al. (2003), i.e. we accept a candidate series as an IMF after five consecutive sifts that meet IMF condition (a). Once the first IMF is identified, it is subtracted from the original series, and the process is repeated on the residual series to extract all IMFs present in the data. In accordance with Peel et al. (2005), we cease IMF extraction when there are a total of ≤3 extrema in the candidate series. At this point, the candidate series represents a residual. The sum of the IMF set, plus the residual, gives the original series.

Methodological Innovations: Splines and Endpoints

Huang et al. (1998) identified areas for improvement to the EMD method, most notably the choice of spline for creation of the upper and lower envelope; and endpoint treatment. In this paper, we use the latest innovations in handling these limitations: rational spline interpolation and endpoint reflectance.

Steps 2 and 3 are crucial to the EMD process, and involve spline-fitting. Early applications of EMD used the traditional cubic spline. However, cubic splines can create over- and under-shooting in the fitting procedure, which can overinflate the variance of the IMFs and the residual (Peel et al. 2007).

As an alternative, Pegram et al. (2008) and Peel et al. (2009) suggested the use of **rational splines**. These have a variable **tension parameter**, *P*, which allows the tautness of the spline to be controlled. The *P* can vary from zero (cubic spline) to larger values where the spline approaches a linear interpolator. Increasing *P* can reduce the variance inflation and cross-correlation of individual IMFs. Minimising IMF cross-correlation is important, because their subsequent use in reconstructing the series for synthetic inflow generation requires the independence assumption to be well-approximated.

By definition, the EMD method is empirical, and experimentation and judgement are required in the selection of the most appropriate *P*. Peel et al. (2009) proposed an Orthogonality Index (OI) as a measure of collective independence of an IMF set. The OI is calculated by scaling the absolute value of the IMF cross products by the detrended residual. As the OI approaches zero, the decomposition approaches orthogonality: hence, according to this measure, an optimal *P* is one that minimises OI.

Sensitivity analyses by Peel et al. (2007) and Peel et al. (2009) have suggested *P* values of 5 and 0-2 respectively as suitable for different rainfall datasets. In this paper, given we are applying rational spline EMD for the first time to hydrological inflows for Melbourne and Sydney, we conducted a broad sensitivity analysis (0≤*P*≤5) on one inflow series (Thomson) which guided more targeted sensitivity analysis (0.5≤*P*≤2) to the remaining inflow series, before individually selecting the most appropriate *P* for each inflow series.

Endpoint treatment was a second area identified by Huang et al. (1998) for methodological improvement to EMD. Because any time series record is of finite length, it is a truncation of a theoretically continuous variable. Without further information, it is not possible to ascertain whether a series endpoint is in fact an extrema. This poses a problem for spline-fitting. Inappropriate treatment can allow the endpoints to fluctuate, which may inadvertently back-propagate artificial waves through a candidate series not observed in the original data. This can progressively corrupt subsequently extracted higher-periodicity IMFs. An initial endpoint technique involved padding the series with additional 'characteristic' or 'typical' waves (Huang et al. 1998). Rilling et al. (2003) mirrorized the extrema closest to the edge. The average of the two closest maxima (minima) for the upper (lower) spline envelope has also been used to deal with the endpoint condition (Chiew et al. 2005). Pegram et al. (2008) used **endpoint reflectance**, which identifies a virtual point that is a reflection of the last extrema point on both ends of the IMF. This technique sets the virtual point to have the same second derivative as the endpoint it mirrors, and is a refinement of Rilling's mirrorizing method. Endpoint reflectance has successfully limited the influence of the endpoints on the IMFs (Peel and McMahon 2006), and is the technique used in this paper. EMD analysis including spline-fitting was conducted in MS Excel using the SplineCalc© software package coded in VB. Supporting metrics were calculated in the R software package.

Hypothesis Testing

Extracting the set of IMFs for a series gives the periodicity of each IMF, and the proportion of total variance accounted for by each IMF. IMFs may also be plotted as time series. These key EMD outputs offer powerful potential for hypothesis testing. In this study, we tested several hypotheses:

Hypothesis 1: a significant proportion of total inflow variance is attributable to IMF periodicities >10 years, indicating the presence of long-run hydrological persistence. Further, reservoir inflows with higher variability exhibit a higher proportion of EMD residual.

Hypothesis 2: long-run hydrological persistence is cross-correlated between reservoir inflows within a region.

Hypothesis 3: coincidence of troughs in multiple IMFs is associated with major droughts (and vice versa). Further, there is a correlation between inflow IMFs and possible causal mechanisms (e.g. hydro-meteorological phenomena such as the SOI).

RESULTS

Sensitivity Analysis

Table 2 shows that for the Thomson inflow series, the OI is minimised (and the number and level of statistically significant individual cross-correlations reduced) using *P* = 2. The more targeted sensitivity analysis (0.5≤*P*≤2) subsequently conducted on the remaining inflow series found that a *P* within the range 0.5-2 provided reasonable scope to maximise individual and collective independence of the IMFs for these reservoir inflow series. These results for hydrological inflows concur with previous applications of EMD to a large sample (n=8135) of annual precipitation time series (Peel et al. 2009). However, as demonstrated in Tables 2 and 3, each reservoir presents unique characteristics which cautions against a 'one size fits all' choice of *P* for a given regional dataset. The result for Upper Yarra warrants further explanation: in this case the *P* with the lowest OI (*P*=2) was not selected. This value extracted five IMFs; however IMFs 3 and 4 exhibited distinguishability issues (as indicated by the individual cross-correlation matrix, and visual inspection of the graphed IMFs). The lower *P* setting (*P*=1) was selected instead, as this extracted four clearly distinguishable IMFs.

Result 1: Presence of long-run persistence

Tables 4 and 5 present the EMD results for the Sydney and Melbourne inflows respectively. Two key results are the IMF periodicities and the proportion of total variance accounted for by each IMF. Collectively, the Melbourne results indicate that 66% of total inflow variance is accounted for by periodicities <10 years: 20% of variance is attributable to periodicities >10 years, with 14% representing a residual. For Sydney, 57% of total inflow variance is accounted for by periodicities <10 years: 21% of variance is attributable to periodicities >10 years, with 22% representing a residual. This is strong evidence supporting Hypothesis 1: long-run persistence is present in these inflows. There is also in general a good correspondence between variability (measured here using the inflow Coefficient of Variation, CV, from Table 1) and the proportion of variance in the residual category. This was apparent at both a regional and (with the exception of Fitzroy Falls) individual inflow level. The Sydney inflows exhibit considerably higher variability relative to the Melbourne inflows.

Table 2: Sensitivity analysis results for Melbourne. Optimal OI (hence P selections) are underscored.

Inflow:	***P*:**					
	0	0.5	1	2	3	5
Thom	0.101	0.103	0.090	0.084	0.135	0.176
UY		0.113	0.099	0.096		
OShan		0.073	0.049	0.081		
Maroon		0.069	0.102	0.044		

Table 3: Sensitivity analysis results for Sydney. Optimal OI (hence P selections) are underscored.

Inflow:	***P*:**	
	0.5	**2**
Warragamba	0.062	0.126
Nepean	0.118	0.059
Cataract	0.087	0.125
Avon	0.035	0.064
Cordeaux	0.049	0.063
Woronora	0.111	0.146
Wingecarribee	0.066	0.102
Fitzroy	0.059	0.049
Tallowa	0.147	0.140

Result 2: Correlation of long-run persistence between reservoir inflows

To test Hypothesis 2, for each region, correlation matrices were produced for the IMFs of similar periodicity (e.g. a correlation matrix was produced for Melbourne IMF1s, IMF2s, etc). Figures 1 and 2 show the histograms of these correlation matrices. This allows visualisation of how inter-reservoir correlation evolves with increasing periodicity. While correlations between IMFs in general decreased with increasing periodicity, Figures 1 and 2 highlight persistent high correlations between select reservoir inflows in both Melbourne and Sydney. For Melbourne, the strongest correlation at periodicities >10 years was between Thomson and Upper Yarra: the two largest Melbourne reservoirs

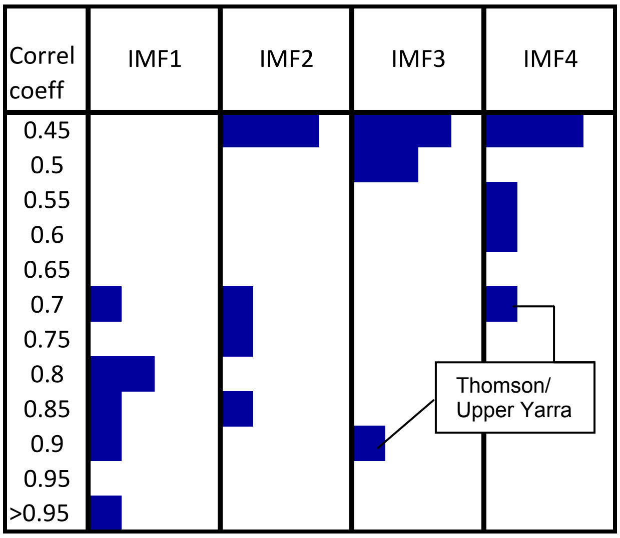

Figure 1: Correlation coefficient histograms for IMFs: Melbourne

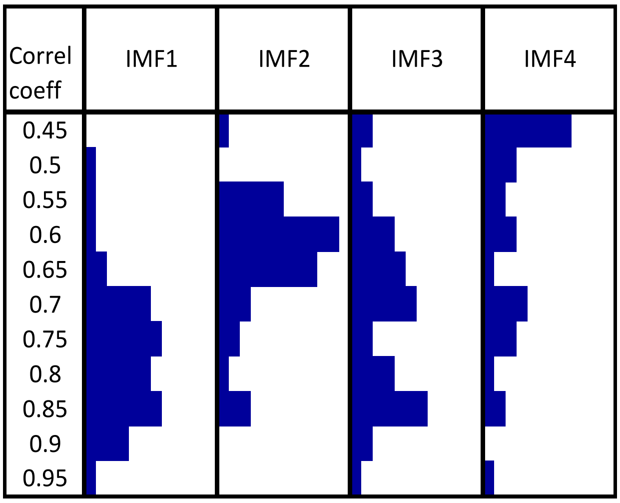

Figure 2: Correlation coefficient histograms for IMFs: Sydney

collectively representing 68% of the Melbourne inflow volumes studied here. An interesting area for future exploration is the relative contributions of scale (reservoir size) and geographic proximity, to this result.

For Sydney, a relatively higher proportion of higher correlations is apparent at higher periodicities. The Nepean-Cataract, Nepean-Wingecarribee and Warragamba-Nepean correlations were >0.80 for IMF4 (mean periodicity=32.01 yrs). Collectively, these reservoirs represent 48% of the Sydney inflows studied here, including three of the largest four.

For both regions, the critical implication for water supply planners is that the relatively high degree of correlation in long-run hydrological persistence between large reservoirs in the surface water supply network amplifies the vulnerability of the city to intense droughts. This poses a risk to water supply reliability in both cities if there is high volumetric reliance on climate-dependent sources (i.e. reservoirs).

Result 3: Trough Coincidence and SOI

Figure 3 plots the time series graph of the EMD IMFs for one representative inflow from each region: Warragamba (Sydney) and Thomson (Melbourne). To test Hypothesis 3, a qualitative trough coincidence analysis was undertaken. Intense drought periods in the hydrological inflows were identified as follows. In each region *r*, transform each total annual inflow series *i* into z-variates (where each z_{it} time series has zero mean and unit variance) for each timestep *t*, before averaging the n_r inflow z-variates each *t*:

$$z_{rt} = \bar{z}_{ri} = \frac{\sum_{i=1}^{n_r}\left(z_{it} = \frac{x_{it} - \bar{x}_i}{SD_i}\right)}{n_r} \qquad (1)$$

then take a five-year rolling average of z_{rt}. Figure 4 plots the result, and allows visualisation of periods of significant negative deviation in inflow records for both regions. Figure 4 indicates intense droughts around 1940, 1970, the early 1980s, and the most recent 'millennial drought' of the early 2000s.

These major drought periods were then compared to the Warragamba and Thomson IMFs in Figure 3, which shows:

- the 1940 drought coincides with troughs in Warragamba IMFs 1, 2 and 4, and Thomson IMF 1;
- the 1970 drought corresponds with troughs in Warragamba IMF3 and 4, and Thomson IMF1 and 2;
- the 1980 drought coincides with troughs in Warragamba IMF2 and 3, and Thomson IMFs 1, 2 and 3; and
- the millennial drought was associated with troughs in Warragamba IMFs 3, 4 and a low residual, and Thomson IMF2 and 3.

The next step is comparison with a potential causal mechanism. As the SOI is one candidate for partial causal mechanism association and attribution, a correlation analysis was undertaken between the reservoir inflow series and the SOI. Monthly SOI values were sourced from the Bureau of Meteorology, and subject to the same EMD analysis as the reservoir inflows. A *P* sensitivity analysis suggested 0.5 was an appropriate setting for the SOI EMD. Eight IMFs were extracted from the monthly SOI series.

The correlation was performed on IMFs from the regional inflows and the SOI IMF that exhibited a similar periodicity: there were three such SOI IMFs. For example, one correlation matrix consisted of the four IMF1s from Melbourne (mean periodicity=3.26 yrs) and SOI IMF5 (periodicity=3.61 yrs). Matrices were generated for three periodicities for each region. Table 6 presents the results, with the stand-out that Sydney exhibited six (out of 9) inflow IMFs, with mean periodicity of 14.18 years, as significantly correlated with the SOI IMF of periodicity 14.62 years. Melbourne exhibited only one inflow IMF as significantly correlated across the three periodicities studied. Collectively, these results provide some evidence in support of Hypothesis 3: trough coincidence is associated with intense drought periods, and, in Sydney, with a plausible causal mechanism examined here (SOI).

Table 6: number of individually significant cross-correlations between regional inflow IMFs and the SOI IMF of similar periodicity

	SOI	MEL	SYD
IMF periodicity [yrs]	3.61	3.26	3.00
# correlations		0	2
IMF periodicity [yrs]	6.62	6.19	6.90
# correlations		1	0
IMF periodicity [yrs]	14.62	13.18	14.18
# correlations		0	6

DISCUSSION

Methodological insights for practitioners

The sensitivity analysis highlights several practical issues in the application of EMD which are helpful for future practitioners. There are tradeoffs involved in selecting an 'optimal' tension parameter. Three considerations were used in this analysis: minimising individual cross-correlations (the number and statistical significance of these); minimising the OI; and finally the partitioning of variance between IMFs. For example: an IMF that makes a marginal contribution to total variance may have no physical meaning. These IMFs may fail the individual cross-correlation statistical test for independence; and further, visual inspection of the periodicity in the resultant time series graphic can suggest the IMF is not sufficiently distinguishable from the previously extracted IMF. A solution in these instances may include trialling a different *P* setting. This analysis also demonstrated that a single, universally-optimal *P* setting for a regional dataset is unlikely, and a unique *P* setting for each data series may be required if the optimal value is sought. Short of this objective, however, *P* settings within a certain range appear to deliver adequate, stable IMF sets with associated statistics.

The broad sensitivity analysis on Thomson inflows illustrates the tradeoff between minimising OI and the number of individually significant cross-correlations between inflow series. While the $P = 0$ setting (the traditional cubic spline, originally (and still extensively) used in EMD) gave the least number of the latter, it did not yield the minimum OI. Difficulty in quantifying the overshooting problem associated with the high-curvature cubic spline is another reason to avoid choice of $P = 0$. However, setting the tension parameter too high ($3 \le P \le 5$) introduced numbers of individually significant cross-correlations. We found that higher *P* settings tended to increase sensitivity to minor deviations towards the endpoints of series: 'tighter' settings gave upper (lower) envelopes that were more likely to under- (over-) cut the curvature (cf. local) extrema in the series, resulting in artificially inflated numbers of extrema. This increased the number of sifts required to extract IMFs (as the stopping criteria were rendered disproportionally harder to meet), leading to over-sifting and extraction of higher-periodicity IMFs which may not be independent. Consideration of these factors affirms choice of $P = 2$ as optimal for the test series (Thomson inflows).

In general, higher tension parameters produced more optimal OI for the Melbourne inflows relative to the Sydney inflows. Based on our observations of the tension parameter sensitivity analysis, we hypothesize that higher tension parameters generate more sifting artefacts in time series that exhibit higher variability. This interpretation is supported by Table 1, which shows that the Coefficient of Variation (CV) of the Melbourne inflows is markedly lower than for Sydney, indicating generally higher variability in the latter series. We aim to further test this hypothesis in the next phase of research, by expanding the sensitivity analysis to include more values of *P*; and through application of EMD to the monthly inflow time series (cf. annual totals used in this analysis). If substantiated, this hypothesis (lower *P* is more suitable for higher-variability series) will guide future practitioners in selecting appropriate tension parameters (based on the descriptive statistics of the series) more expeditiously.

Future Work

This paper presented a limited and qualitative trough coincidence analysis, as an example of a subsequent application that is possible with EMD results. Further quantitative work is required to strengthen the qualitative results presented here, and an examination of lag effects between variables can be quantitatively modelled using time series analysis. However, these initial results are useful in demonstrating sufficient potential to warrant quantitative follow-up, including with a wider range of potential, partial causal mechanisms (e.g. IPO).

There are opportunities to explore the relationship between the EMD results presented here, and other estimation methods for long-run hydrological persistence (e.g. the Hurst exponent). EMD is most suited to long records, and the potential to apply EMD to extended palaeo datasets is also under consideration.
Lastly: the EMD results presented here were produced using total annual inflows. However, the

inflow data are available at monthly timesteps, and it would be interesting to repeat the EMD analysis with this finer timestep resolution to test the robustness of the IMF results. If total annual inflow data are used by practitioners in future analyses, consideration may be given to aggregating the inflow data into water year (cf. calendar year).

CONCLUSION

This paper used EMD to characterise hydrological persistence in historical reservoir inflows supporting the cities of Melbourne and Sydney. Hydrological persistence in these series occurs over a range of scales, and includes periodic components (IMFs). The analysis showed that long-run hydrological persistence accounts for a considerable proportion of total variance in hydrological inflows, with 20% of variance in Melbourne region inflows and 21% of Sydney region inflows associated with periodicities >10 years. Further, these long-run components of hydrological persistence exhibited some strong cross-correlations between inflow series within a region. Finally, a preliminary application found that coincidence of troughs in multiple IMFs are associated with intense drought periods, and show statistically significant correlations with a plausible, partial causal mechanism (SOI). Collectively, these results highlight the water supply reliability risk to which these cities are exposed if high reliance is placed on climate-dependent water supplies (i.e. reservoir inflows). The results underscore the need for water supply planners to incorporate long-run hydrological persistence into future reliability modelling, and imply that reliability modelling over shorter time horizons which neglects long-run hydrological persistence may be deficient in estimating reliability.

EMD provides a powerful and accessible technique to visualise and quantify hydrological persistence over a range of scales. The next phase of this research project will harness these EMD results to generate synthetic inflow sequences (which include the identified components of hydrological persistence) to model these cities' water supply reliability under future scenarios of climate change and a mix of water supply portfolio options.

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Table 4: EMD results for Sydney

Metric:			IMF1	IMF2	IMF3	IMF4	Residual	Inflow:	*P:*
Periodicity [yrs]:			2.77	6.30	13.00	29.71		Warra	0.5
			3.01	6.93	13.87	29.71		Nep	2
			3.10	7.70	13.87	29.71		Cat	0.5
			3.10	7.17	14.86	41.60		Avon	0.5
			3.10	8.32	18.91	N/A		Cord	0.5
			3.10	6.93	13.87	29.71		Woro	0.5
			3.01	6.12	12.24	26.00		Wing	0.5
			2.76	6.32	14.00	28.00		Fitz	0.5
			3.01	6.30	13.00	41.60		Tall	2
		$\bar{x}$:	**3.00**	**6.90**	**14.18**	**32.01**			
Proportion of total variance:	Σ	100%	34.98%	15.04%	10.24%	13.03%	26.72%	Warra	0.5
		100%	44.45%	20.15%	12.45%	5.42%	17.53%	Nep	2
		100%	44.35%	26.34%	13.23%	6.84%	9.24%	Cat	0.5
		100%	34.06%	22.97%	10.41%	10.21%	22.35%	Avon	0.5
		100%	34.41%	30.87%	12.04%	0.00%	22.68%	Cord	0.5
		100%	29.74%	15.61%	22.19%	13.69%	18.77%	Woro	0.5
		100%	51.68%	14.96%	11.27%	2.96%	19.12%	Wing	0.5
		100%	31.64%	12.68%	18.25%	2.63%	34.80%	Fitz	0.5
		100%	38.12%	8.89%	13.98%	14.45%	24.56%	Tall	2
		$\bar{x}$:	**38.16%**	**18.61%**	**13.79%**	**7.69%**	**21.75%**		

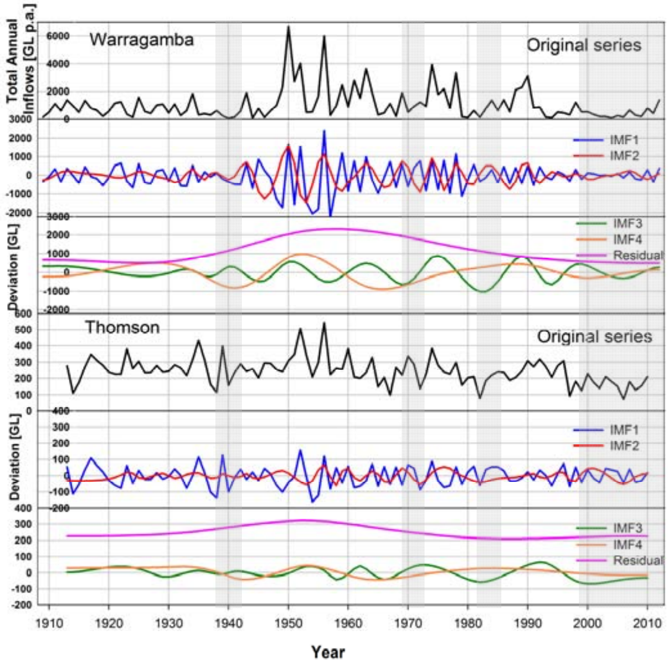

Figure 3: EMD IMFs of Warragamba and Thomson inflows. Shading indicates drought periods from Figure 4.

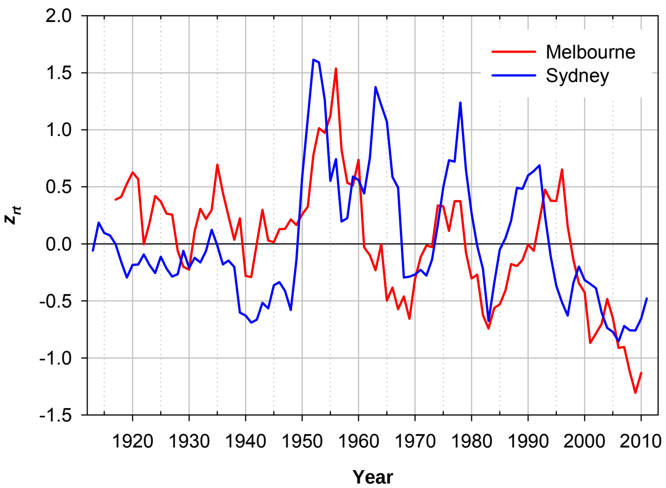

Figure 4: Five-year rolling average of the mean z-variates of total annual inflows to 9 Sydney reservoirs and 4 Melbourne reservoirs

Table 5: EMD results for Melbourne

Metric:			IMF1	IMF2	IMF3	IMF4	Residual	Inflow:	*P:*
Period-icity [yrs]:			3.27	6.76	15.08	39.20		Thom	2
			3.32	6.13	15.08	28.00		UY	1
			3.32	6.13	12.25	24.50		OShan	1
			3.11	5.76	10.32	24.50		Maroon	2
		$\bar{x}$:	**3.26**	**6.19**	**13.18**	**29.05**			
Proportion of total variance:	Σ	100%	50.43%	9.79%	14.47%	8.32%	16.98%	Thom	2
		100%	54.35%	7.72%	12.76%	7.43%	17.74%	UY	1
		100%	56.67%	11.00%	7.77%	8.59%	15.97%	OShan	1
		100%	58.32%	14.93%	10.70%	9.97%	6.08%	Maroon	2
		$\bar{x}$:	**54.94%**	**10.86%**	**11.43%**	**8.58%**	**14.19%**		