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*Guglielmo Maria Caporale, Luis A. Gil-Alana, Laura Sauci*

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## Abstract

This paper analyses US sea level data using long memory and fractional integration methods. All series appear to exhibit orders of integration in the range (0, 1), which implies long-range dependence; further, significant positive time trends are found in the case of 29 stations located on the East Coast and the Gulf of Mexico, and negative ones in the case 4 stations on the North West Coast, but none for the remaining 8 on the West Coast. The highest degree of persistence is found for the West Coast and the lowest for the East Coast.

JEL-Codes: C210, Q540.

Keywords: sea level, time trends, fractional integration.

*Guglielmo Maria Caporale**
*Department of Economics and Finance*
*Brunel University London*
*United Kingdom – London, UB8 3PH*
*Guglielmo-Maria.Caporale@brunel.ac.uk*

*Luis A. Gil-Alana*
*University of Navarra*
*Pamplona / Spain*
*alana@unav.es*

*Laura Sauci*
*UNED*
*Madrid / Spain*

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## 1. Introduction

In the last few decades, considerable efforts have been made to gain a deeper understanding of the effects of global climatic variations on the sea level, which is essential to prevent potential coastal flood hazards and mitigate their socio-economic and environmental consequences. Of particular interest are the Assessment Reports of the Intergovernmental Panel on Climate Change (IPCC). The empirical evidence from the First Assessment Report (FAR) published in 1990 to the most recent IPCC work (Oppenheimer, 2019) indicates that there has been a global mean sea level (GMSL) rise of 1.0–2.0 mm year$^{-1}$ during the 20$^{th}$ century, which is much larger than in the previous two centuries (Warrick and Oerlemans, 1990), and in the last two millennia as a whole (IPCC, 2014: 4). In particular, the GMSL rise estimated from tide gauge data is of 1.5 [1.1–1.9] mm year$^{-1}$, with an acceleration range of [-0.002–0.019] over the period 1902–2010, while the revised estimate from satellite altimetry data is 3.16 [2.79–3.53] mm year$^{-1}$, with an acceleration of 0.084 [0.059–0.090] mm year$^{-1}$ over 1993–2015 (see Church et al., 2013; WCRP Global Sea Level Budget Group, 2018; Oppenheimer et al., 2019).

However, this increase has not been uniform around the world. In particular, in the case of the US there are important differences between the Eastern and Western coastline. The National Oceanic and Atmospheric Administration (NOAA), in its technical report NOS CO-OPS 053 (Zervas, 2009) examined the linear mean sea level trends in 128 stations located on the US Atlantic and Pacific coasts, Alaska and the Gulf of Mexico, among other areas. According to this report, the upward trend in the regional sea level for the majority of the East coast stations implies a rate of increase above the 20$^{th}$ century GMSL rise of 1.7 mm year$^{-1}$, the highest value (6.05 mm year$^{-1}$) being estimated for the Chesapeake Bay Bridge Tunnel station. By contrast, in the case of the

West coast the increase is around or below the GMSL rise of 1.7 mm year$^{-1}$. The highest regional sea levels increases have been observed in Louisiana, Eastern Texas and the stretch from Virginia to New Jersey, which can be explained by Gulf Stream variations, land subsidence and tectonic movements (Zervas, 2009; Sweet et al., 2017).

Future scenarios for the sea level rise are based on emissions and the associated risks. It is expected that GMSL will continue increasing during the 21$^{st}$ century with mean values of 0.43 [0.29–0.59], 0.55 [0.39–0.72] and 0.84 [0.61–1.10] for the Representative Concentration Pathway models (RCP)2.6, RCP4.5 and RCP8.5, respectively. Sweet et al. (2017) updated the future scenarios for the GMSL rise presented in Parris et al. (2012), and specified six possible 2100 scenarios ranging from 0.3m (Low) to 2.5m (Extreme). More specifically, in the Intermediate-High (1.5-m GMSL rise) scenario the (high-low) increase would be 0.4–0.7 m (higher than the GMSL rise) for the US East Coast and 0.2–0.3 m (higher than the GMSL rise) for the West Coast.

All the available empirical evidence suggests a continuing upward trend in the sea level despite possible future reductions of anthropogenic emissions, which since 1970 have been the key factor determining ocean warming (Church et al., 2001; Oppenheimer et al., 2019). Hence, it is vital to gain further insights into this issue that can contribute to an effective decision-making and design of government policies. For this purpose, given the long-memory property characterising most geophysical and climatological time series - see, e.g., Percival et al., 2001; Gil-Alana, 2006, 2015, 2017; Ercan et al., 2013; Bunde 2017; Yuan et al., 2013, 2019), this paper applies a fractional integration approach to obtain new findings on sea level trends for different tide gauge stations on the US coastline. The layout of the paper is the following: Section 2 provides a brief review of the relevant literature; Section 3 describes the data and the methodology; Section 4 presents the empirical results; Section 5 offers some concluding remarks.

## 2. Literature Review

The analysis of sea level trends provides useful information about its variability in the past, present and future. Multiple factors can drive global and regional sea level changes such as atmospheric and ocean warming, tectonic dynamics or anthropogenic forces. In particular, recent studies point to ocean-thermal expansion, glaciers and the Greenland and Antarctic ice sheets and terrestrial water store, as the main factors behind the GMSL rise during the 20$^{th}$ century and in the present (Warrick and Oerlemans, 1990; Church et al., 2013; Church and Gregory, 2019; Oppenheimer et al., 2019). There is an ongoing debate about the possible 'acceleration-deceleration' (Church and White, 2006; Woodworth et al., 2009; Houston and Dean, 2011; Boon, 2012; Jevrejeva et al., 2014; Visser et al., 2015; Boon and Mitchell, 2015; Watson, 2016; etc.) or the 'intrinsic/natural-anthropogenic' nature of sea level changes (Jevrejeva et al.,, 2009; Lennartz and Bunde, 2012; Becker et al., 2014; Dangendorf et al., 2014, 2015; Slangen et al., 2016; Marcos et al., 2016; etc.); on the whole, it appears that anthropogenic factors have been the main cause of the sea level rise since 1970 (Oppenheimer et al., 2019).

Sea level variability is a complex issue that should be analysed carefully given the limitations of tide gauge and satellite altimetry data and the variety of applicable statistical techniques. The most common approach is trend analysis. Comprehensive surveys are provided by Mudelsee (2010), Chandler and Scott (2011) and Visser et al. (2015), who classify existing studies as using parametric, nonparametric or stochastic trend models respectively. Regarding this last approach, stochastic long-memory processes appear to be the most appropriate for geophysical/climate time series, since these tend to exhibit long-run dependence (LRD) or temporal correlations (Beran, 1994; Percival et al., 2001; Gil-Alana, 2006; Ercan et al., 2013; Graves et al., 2017). Such models range from those proposed by Hurst (1951) in hydrology, and later by Mandelbrot (1967) and Mandelbrot and Van Ness (1968) for self-similarity and the fractal dimension, to the AutoRegressive Fractionally Integrated Moving Average (ARFIMA) model of Granger and Joyeux (1980), and its subsequent extensions.

Long-memory models have been widely used for climate variables such as temperature (Bloomfield, 1992; Caballero et al., 2002; Franzke, 2012; Gil-Alana, 2005, 2008, 2018), but less for sea level data. In particular, there is very limited evidence concerning US tide gauge records. Jiang and Plotnick (1998) were the first to carry out fractal analysis using US coastline data with a continental dimension; applying the divider method (Mandelbrot, 1982), they found more complexity in terms of the fractal dimension for the Atlantic coast, and also a significant correlation with latitudes, less complexity characterising lower latitudes. The fractal dimension ranges for Atlantic and Pacific shorelines are [1.0-1.70] and [1.0-1.27], respectively; in particular, Chesapeake Bay, the St. Johns River of Florida, and the Florida Keys, in the Atlantic coast, exhibit most complexity. Barbosa et al. (2008) considered 16 North Atlantic stations; employing three statistical approaches (parametric stationary tests, wavelet analysis and Generalized Least Squares (GLS)), they found LRD in all cases except Newlyn; in particular, they detected high persistence for Portland, Boston, Newport and New York that might reflect local/regional differences, as in the case of Chesapeake Bay (Kiptopeke, Hampton), which is characterised by subsidence and tectonic movements. However, according to Koop (2013), the rate of US mid-Atlantic sea level rise is within its historical variability.

In another recent study, Dangendorf et al. (2014) investigated sea level changes using 60 monthly average tide gauge records around the world. Their results from the Detrended Fluctuation Analysis -DFA2- (Kantelhardt et al., 2001) show, for all records, a LRD up to 35 years, which suggests the importance of the internal behaviour to understand sea level changes. By contrast, Becker et al. (2014) concluded that global and regional sea level changes are strongly driven by anthropogenic forces, in particular in the case of New York, Baltimore and San Diego. Finally, Royston et al. (2018) addressed the issue of residual noise when estimating linear trends, and showed that it is coloured but non-AR(1) in the majority of cases, the AR(1) model being more appropriate for shorter series (Bos et al., 2014). The inclusion of climate indices in the regression does not affect the choice of noise model: for San Francisco and Seattle, the preferred noise models are ARFIMA specifications, with a trend coefficient (including climate indices) of 2.37 and 2.71, respectively, while for Honolulu, the preferred model is the Generalized Gauss Markov (GGM) noise model, with an estimated trend coefficient of 1.29. The study by Royston et al. (2018) is the closest to ours, since we also consider long-range dependence models based on fractional integration and estimate the time trend coefficients allowing the errors to be fractionally integrated.

## 3. Data and Methodology

The data examined concern 41 US stations covering most of the US coast. Table 1 reports the names of the stations and the percentage of coverage; we only consider series with a maximum of 10% missing data, and compute them as a simple arithmetic mean of the previous and following monthly value in the series. The data are available at https://www.psmsl.org/data/obtaining/.

**TABLE 1 HERE**

The fractional integration approach we use is more general than others such as ARMA/ARIMA models since it does not restrict the difference parameter to take an integer value. The standard approach estimates a linear time trend in the following regression model:

$$y_t \;=\; \alpha \;+\; \beta t \;+\; x_t\,, \qquad (1)$$

where a significant slope coefficient β implies the presence of a trend (positive or negative, depending on the sign of the coefficient). However, this set-up implicitly assumes that the error term, $x_t$ is integrated of order 0 or I(0). This implies not only that it must be covariance-stationary, but also that the infinite sum of its autocovariances must be finite. This property is satisfied by the classical ARMA-type of models. If it is not, for example if the data display a high degree of persistence, first differences are then taken, on the assumption that $x_t$ is integrated of order 1 or I(1). Thus, $x_t$ is specified such that $(1 – B)x_t = u_t$, where B is the backshift operator ($Bx_t = x_{t-1}$) and $u_t$ is I(0). However, as already mentioned in Section 2, it is well known that many time series, especially climatological ones, are neither I(0) nor I(1) but I(d) where d is a fractional value. This is approach taken in the present study.

Specifically, we estimate the time trend coefficient β and the fractional differencing parameter d (along with the other parameters) in the following regression model:

$$y_t \;=\; \alpha \;+\; \beta t \;+\; x_t\,, \qquad (1 - B)^d\; x_t \;=\; u_t\,, \qquad u_t \;=\; \rho\, u_{t-12} \;+\; \varepsilon_t\,. \qquad (2)$$

where $y_t$ is the observed time series; α and β are unknown coefficients, namely the intercept (constant) and the linear time trend coefficient; $x_t$ stands for the regression errors, assumed to be I(d), which implies that $u_t$ is I(0); moreover, given the possible seasonality of the monthly data analysed, a seasonal (monthly) AR(1) process is assumed for the I(0) disturbances $u_t$, where ρ is the seasonality indicator.

For the estimation, we use a Whittle function in the frequency domain following the testing approach of Robinson (1994), thus allowing for any real value d, including values in the non-stationary range (i.e., $d \geq 0.5$ - see Gil-Alana and Robinson (1997) for a description of the version of the tests of Robinson (1994) used in this application).

## 4. Empirical Results

Table 2 displays the estimated values of d from equation (2) under three different assumptions:

i) no deterministic components, i.e., imposing $\alpha = \beta = 0$

ii) a constant only, i.e., with $\beta = 0$

iii) a constant and a linear time trend

Along with the estimated values of d, which are a measure of persistence, we also report their 95% confidence bands, which correspond exactly to the band of non-rejection values calculated as in Robinson (1994); the coefficients in bold are those from our preferred specification, which has been selected on the basis of the statistical significance of the deterministic terms; these are also reported in Table 3 together with the estimated $\alpha$ (constant), $\beta$ (time trend coefficient) and $\rho$ (seasonality).

**TABLES 2 AND 3 HERE**

It can be seen from Table 2 that significant time trends are found in 29 cases out of 41; of those, only in four cases (Neah Bay, Juneau, Sitka and Yakutat) the trend is negative, being otherwise positive, with the estimated coefficient ranging from 0.158 (Portland Maine) to 0.745 (Grand Isle). The four stations with a negative trend are located on the North West coast, whilst those with a positive trend (25) are located on the East coast and the Gulf of Mexico; the 12 stations with an insignificant trend are all on the West coast (see Table 4 and Figure 1).

**TABLE 4 AND FIGURE 1 HERE**

All the estimated values of d are in the interval (0, 1) and range between 0.29 (Annapolis, Naval Academy) and 0.75 (La Jolla, Scripps Piers), which confirms that the series are fractionally integrated. The series can be divided into three categories according to their degree of persistence: those with values of d in the range (0, 0,5), that is, covariance-stationary series; those with values around 0.5, on the boundary between stationarity and non-stationarity; a third group with values in the interval [0.5, 1), which implies non-stationary mean-reverting behaviour (see Table 5 and Figure 2)

**TABLE 5 AND FIGURE 2 HERE**

It can be seen that 22 stations are in the first category with a low degree of persistence, and virtually all of them are located on the East coast; for 12 stations the estimated value of d implies that they belong to the intermediate category, and these are all located on the Gulf of Mexico or the West coast; 7 stations are in the non-stationary range ($d \geq 0.5$), all them on the West coast, and since the estimated value of d is significantly below 1 mean-reversion occurs, with the effects of shocks dying away in the long run.

## 5. Conclusions

This paper examines US sea level data for a set of 41 stations chosen on the basis of data availability and covering most of the US coastline. A fractional integration framework is applied to test for the presence of trends and the degree of persistence. The results indicate that all series are fractionally integrated, since their differencing parameter is estimated to lie in the interval (0, 1). More specifically, there is evidence of long-memory stationarity (i.e., $0 < d < 0.5$) for 22 stations, most of them located on the East coast; for 12 stations the order of integration is around 0.5, and for 7 (all located on the West coast) there is evidence of non-stationary mean-reverting patterns ($0.5 \leq d < 1$).

There are significant time trends in 29 out of the 41 cases examined (positive in 25 cases and negative in 4). The stations with a positive trend are located on the East coast and the Gulf of Mexico, while the four with a negative trend (Neah Bay, Juneau, Sitka and Yakutat) are located on the North West coast. These findings imply that there is a clear rise in the US sea level only in the case the East coast and the Gulf of Mexico, and therefore the authorities should focus on those to address the issue of an increasing sea level. This conclusion is also corroborated by the estimated degree of persistence, which is higher for the East coast stations, suggesting that the effects of shocks will be more long-lived in their case.

**References**


Barbosa, S.M., Silva, M.E., and Fernandes, M.J. (2008). Time series analysis of sea-level records: Characterising long-term variability. In: Donner R.V., Barbosa S.M. (eds) Nonlinear Time Series Analysis in the Geosciences. Lecture Notes in Earth Sciences, 112, 157-173.

Becker, M., Karpytchev, M., and Lennartz-Sassinek, S. (2014), Long-term sea level trends: Natural or anthropogenic? Geophysical Research Letters, 41, 5571– 5580.

Beran, J. (1994). Statistics for long-memory processes. Chapman & Hall: New York, NY, USA, 1–315.

Bloomfield, P. (1992) Trends in global temperatures. Climatic Change, 21(1), 275–287.

Boon, J.D. and Mitchell, M., (2015). Nonlinear change in sea level observed at North American tide stations. Journal of Coastal Research, 31(6), 1295–1305.

Boon., J.D. (2012). Evidence of Sea Level Acceleration at U.S. and Canadian Tide Stations, Atlantic Coast, North America. Journal of Coastal Research, 1437-1445.

Bos, M.S., Williams, S.D.P., Araujo, I.B., and Bastos, L. (2014). The effect of temporal correlated noise on the sea level rate and acceleration uncertainty, Geophysical Journal International, 196, 1423–1430.

Bunde, A. (2017) Long-term memory in climate: Detection, extreme events and significance of trends, Chapter 11 in Nonlinear and Stochastic Climate Dynamics, edited by Christian L. E. Franzke and Terence O'Kane: Cambridge University Press.

Caballero, R., Jewson, S. and Brix, A. (2002) Long memory in surface air temperature: detection, modelling, and application to weather derivative valuation. Climate Research, 21(2), 127–140.

Chandler, R.E., and Scott, E.M.(2011). Statistical methods for trend detection and analysis in the environmental science. A John Wiley & Sons, Ltd., Publication, 1-368.

Church, J. A. and White, N. J. (2006). A 20$^{th}$ century acceleration in global sea-level rise. Geophysical Research Letters, 33(1), L01602.

Church, J., Clark, P., Cazenave, A., Gregory, J., Jevrejeva, S., Levermann, A., Merrifield, M., Milne, G., Nerem, R., Nunn, P., Payne, A., Pfeffer, W., Stammer, D., Alakkat, U. (2013). In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Sea Level Change. 1138–1191.

Church, J.A., and Gregory, J.M. (2019). Sea Level Change. Reference Module in Earth Systems and Environmental Sciences Encyclopedia of Ocean Sciences (Third Edition), 6, 493-499.

Church, J.A., Gregory, J.M., Huybrechts, P., Kuhn, M., Lambeck, K., Nhuan, M.T., Qin, D., and Woodworth, P.L. (2001). Changes in Sea Level. In: Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change [Houghton, J.T.,Y. Ding, D.J. Griggs, M. Noguer, P.J. van der Linden, X. Dai, K. Maskell, and C.A. Johnson (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 881pp.

Dangendorf , S., Rybski, D., Mudersbach, C., Müller, A., Kaufmann, E., Zorita, E., Jensen, J.(2014). Evidence for long-term memory in sea level, Geophysical Research Letters, 41, 5530–5537.

Dangendorf, S., Marcos, M., Muller, A., Zorita, E., Riva, R., Berk, K., Jensen, J. (2015) Detecting anthropogenic footprints in sea level rise. Nature Communications, Macmillan Publishers Limited, 6(1), 1–9.

Dangendorf, S., Rybski, D., Mudersbach, C., Müller, A., Kaufmann, E., Zorita, E., and Jensen, J. (2014). Evidence for long-term memory in sea level. Geophysical Research Letters, 41, 5530–5537.

Ercan, A., Kavvas, M.L., Abbasov, R.K. (2013). Long-range dependence and sea level forecasting. Springer International Publishing, 1-51.

Franzke, C. (2012) Nonlinear trends, long-range dependence, and climate noise properties of surface temperature. Journal of Climate, 25(12), 4172–4183.

Gil-Alana, L.A. (2005) Statistical model for the temperatures in the Northern hemisphere using fractional integration techniques. Journal of Climate, 18(24), 5537–5369.

Gil-Alana, L.A. (2006) Nonstationary, long memory and antipersistence in several climatological time series data. Environmental Modeling and Assessment, 11(1), 19–29.

Gil-Alana, L.A. (2008) Time trend estimation with breaks in temperature time series. Climatic Change, 89(3–4), 325–337.

Gil-Alana, L.A. (2015) Linear and segmented trends in sea surface temperature data. Journal of Applied Statistics, 42(7), 1531–1546.

Gil-Alana, L.A. (2017) Alternative modelling approaches for the ENSO time series. Persistence and seasonality. International Journal of Climatology, 37(5), 2354–2363.

Gil-Alana, L.A. (2018) Maximum and minimum temperatures in the United States: Time trends and persistence. Atmospheric Science Letters, 19(4), 810–813.

Gil-Alana, L.A. and Robinson, P.M. (1997). Testing of Unit Roots and Other Nonstationary Hypotheses in Macroeconomic Time Series, Journal of Econometrics 80, 241–268.

Granger C.W.J., and Joyeux, R. (1980). An introduction to long memory time series models and fractional differencing, Journal of Time Series Analysis 1, 15–29.

Graves, T., Gramacy, R., Watkins, N., and Franzke, C. (2017). A brief history of long memory: Hurst, Mandelbrot and the road to ARFIMA, 1951-1980. Entropy, 19(9) 437, 1–21.

Houston, J. and Dean, R. (2011). Sea-level acceleration based on U.S. tide gauges and extensions of previous global-gauge analysis. Journal of Coastal Research 27 (3):409–417.

Hsui, A.T., Rust, K.A., and Klein, G.D. (1993). A fractal analysis of Quaternary, Cenozoic-Mesozoic, and Late Pennsylvanian sea level changes, Journal of Geophysical Research, 98( B12), 21963– 21967.

Hurst, H.E. (1951) Long-term storage capacity of reservoirs. Transactions of the American Society of Civil Engineers, 116(1), 770-799.

Jevrejeva, S., Grinsted, A., and Moore, J.C. (2009), Anthropogenic forcing dominates sea level rise since 1850, Geophysical Research Letter,36, L20706, 1–5.

Jevrejeva, S., Moore, J.C., Grinsted, A., Matthews, A.P., and Spada, G. (2014). Trends and acceleration in global and regional sea levels since 1807. Global and Planetary Change, 113, 11–22.

Jiang, J., and Plotnick, R.E. (1998). Fractal analysis of the complexity of United States Coastlines. Mathematical Geology, 30(5), 535-546.

Kantelhardt, J. W., E. Kocielny-Bunde, H. A. Rego, S. Havlin, and A. Bunde (2001), Detecting long-range correlations with detrended fluctuation analysis, Phys. A, 295, 441–454.

Koop, R.E. (2013). Does the mid-Atlantic United States sea level acceleration hot spot reflect ocean dynamic variability?. Geophysical Research Letters, 40(15), 3981-3985.

Lennartz, S. and Bunde, A. (2012). On the Estimation of Natural and Anthropogenic Trends in Climate Records. Washington DC American Geophysical Union Geophysical Monograph Series. 196. 177–189.

Mandelbrot, B. (1967). How long is the coast of Britain? Statistical self-similarity and fractional dimension," Science 155, 636-638.

Mandelbrot, B. (1982). The Fractal Geometry of Nature. W. H. Freeman and Company.

Mandelbrot, B.B., van Ness, J.W. (1968). Fractional Brownian motions, fractional noises and applications. SIAM Review 10, 422–437.

Marcos, M., Marzeion, B., Dangendorf, S., Slangen, A.B.A., Palanisamy, H., and Fenoglio-Marc, L. (2016). Internal variability versus anthropogenic forcing on sea level and its components. Surveys in Geophysics, 38(1), 329–348.

Mudelsee, M. (2010). Climate time series analysis. Classical statistical and bootstrap methods. 2nd ed., Springer, Dordrecht.

Oppenheimer, M., Glavovic, B.C., Hinkel, J., van de Wal, R., Magnan, A.K., Abd-Elgawad, A., Cai, R., Cifuentes-Jara, M., DeConto, R.M., Ghosh, T., Hay, J., Isla, F., Marzeion, B., Meyssignac, B., and Sebesvari, Z. (2019). Sea Level Rise and Implications for Low-Lying Islands, Coasts and Communities. In: IPCC Special Report on the Ocean and Cryosphere in a Changing Climate, 321–446.

Parris, A., Bromirski, P., Burkett, V., Cayan, D., Culver, M., Hall, J., Horton, R., Knuuti, K., Moss, R., Obeysekera, J., Sallenger, A., and Weiss, J. (2012). Global Sea Level Rise Scenarios for the US National Climate Assessment. NOAA Tech Memo OAR CPO-1. 37 pp.

Percival, D.B., Overland, J.E. and Mofjeld, H.O. (2001) Interpretation of North Pacific variability as a short- and long-memory process. Journal of Climate, 14(24), 4545–4559.

Robinson, P.M. (1994). Efficient Tests of Nonstationary Hypotheses, Journal of the American Statistical Association 89, 1420–1437.

Royston, S., Watson, C.S., Legrésy, B., King, M.A., Church, J.A., & Bos, M.S. (2018). Sea-level trend uncertainty with Pacific climatic variability and temporally-correlated noise. Journal of Geophysical Research: Oceans, 123, 1978–1993.

Slangen, A.B.A., Church, J.A., Agosta, C., Fettweis, X., Marzeion, B., and Richter, K. (2016). Anthropogenic forcing dominates global mean sea-level rise since 1970. Nature Climate Change 6, 701–705.

Sweet, W.V., Kopp, R.E., Weaver, C.P., Obeyskera, J., Horton, R.M., Thieler, E.R., and Zervas, C. (2017). Global and regional sea level rise scenarios for the United States, NOAA Technical Report NOS CO-OPS083.

Visser, H., Dangendorf, S. and Petersen, A.C. (2015). A review of trend models applied to sea level data with reference to the “acceleration-deceleration debate”, Journal of Geophysical Research: Oceans, 120,

Visser, H., Dangendorf, S., and Petersen, A.C. (2015). A review of trend models applied to sea level data with reference to the “acceleration–deceleration debate”, Journal of Geophysical Research: Oceans, 3873– 3895.

Warrick, R. A., and Oerlemans, J. (1990). Sea level rise. In: Climate Change: The IPCC Scientific Assessment [Houghton, J.T., Jenkins, G.J., and Ephraum, J.J. (eds.)]. Cambridge University Press, Cambridge, United Kingdom, and New York, NY, USA, 260–281.

Watson, P.J., 2016. Acceleration in U.S. mean sea level? A new insight using improved tools. Journal of Coastal Research, 32(6), 1247–1261.

WCRP Global Sea Level Budget Group, 2018: Global sea level budget 1993-present. Earth Syst. Sci. Data, 10(3), 1551–1590.

Woodworth, P.L.; White, N.J.; Jevrejeva, S.; Holgate, S.J.; Church, J.A., and Gehrels, W.R., 2009. Evidence for the accelerations of sea level rise on multi-decade and century timescales. International Journal of Climatology, 29, 777–789.

Yuan, N., Fu, Z. and Liu, S. (2013) Long-term memory in climate variability: A new look based on fractional integral techniques. Journal of Geophysical Research: Atmospheres, 118(12), 962–969

Yuan, N., Huang, Y., Duan, J., Zhu, C., Xoplaki, E. and Luterbacher, J. (2019) On climate prediction; how much can we expect from climate memory? Climate Dynamics, 52(1–2), 855–864.

Zervas, C. (2009). Sea level variations of the United States 1854-2006. NOAA Technical Report NOS CO-OPS 053.

**Table 1: Time series examined and abbreviations**

| Series | Name | % of observed data |
|---|---|---|
| 10_SF | 10_SAN FRANCISCO | 100.00% |
| 12_NY | 12_NEW YORK (THE BATTERY) | 98.79% |
| 112_FEB | 112_FERNANDINA BEACH | 96.13% |
| 127_STT | 127_SEATLE | 99.87% |
| 135_PHI | 135_PHILADELPHIA (PIER 9N) | 97.46% |
| 148_BAL | 148_BALTIMORE | 99.63% |
| 155_HON | 155_HONOLULU | 100.00% |
| 158_SDG | 158_SAN DIEGO (QUARANTINE STATION) | 98.065 |
| 180_ATL | 180_ATLANTIC CITY | 92.14% |
| 183_POR | 183_PORTLAND (MAINE) | 99.63% |
| 188_KW | 188_KEY WEST | 98.79% |
| 225_KET | 225_KETCHIKAN | 98.42% |
| 234_CHA | 234_CHARLESTON I | 100.00% |
| 235_BOS | 235_BOSTON | 98.67% |
| 245_LA | 245_LOS ANGELES | 98.67% |
| 246_PEN | 246_PENSACOLA | 98.06% |
| 256_JOL | 256_LA JOLLA (SCRIPPS PIER) | 97.34% |
| 265_AST | 265_ASTORIA (TONGUE POINT) | 100.00% |
| 311_ANN | 311_ANNAPOLIS (NAVAL ACADEMY) | 95.04% |
| 332_EAST | 332_EASTPORT | 91.66% |
| 351_NEW | 351_NEWPORT | 98.55% |
| 360_WAS | 360_WASHINGTON DC | 97.82% |
| 366_SAN | 366_SANDY HOOK | 97.82% |
| 367_WOO | 367_WOODS HOLE (OCEAN. INST.) | 93.23% |
| 378_CRES | 378_CRESCENT CITY | 98.43% |
| 384_FRI | 384_FRIDAY HARBOR (OCEAN. LABS.) | 97.82% |
| 385_NEA | 385_NEAH BAY | 97.34% |
| 395_FOR | 395_FORT PULASKI | 98.55% |
| 396_WIL | 396_WILMINGTON | 98.18% |
| 405_JUN | 405_JUNEAU | 100.00% |
| 412_SOL | 412_SOLOMONS ISLAND (BIOL. LAB.) | 95.29% |
| 426_SIT | 426_SITKA | 99.39% |
| 428_CED | 428_CEDAR KEY II | 94.44% |
| 429_NL | 429_NEW LONDON | 95.89% |
| 437_ALA | 437_ALAMEDA (NAVAL AIR STATION) | 99.27% |
| 445_YAK | 445_YAKUTAT | 95.89% |
| 497_ISA | 497_PORT ISABEL | 96.01% |
| 508_LUIS | 508_PORT SAN LUIS | 94.20% |
| 519_MON | 519_MONTAUK | 91.42% |
| 520_PET | 520_ST. PETERSBURG | 99.87% |
| 526_GRA | 526_GRAND ISLE | 95.41% |

**Table 2: Estimates of d in the model given by equation (*)**

| Series | No deterministic terms | An intercept | An intercept and a linear time trend |
|---|---|---|---|
| 10_SF | 0.99 (0.94, 1.04) | **0.58 (0.51, 0.66)** | 0.58 (0.51, 0.66) |
| 12_NY | 0.98 (0.93, 1.03) | 0.40 (0.34, 0.47) | **0.38 (0.31, 0.47)** |
| 112_FEB | 0.96 (0.91, 1.02) | 0.33 (0.26, 0.41) | **0.32 (0.24, 0.42)** |
| 127_STT | 0.97 (0.93, 1.03) | **0.42 (0.35, 0.52)** | 0.42 (0.34, 0.52) |
| 135_PHI | 0.97 (0.92, 1.03) | 0.39 (0.32, 0.46) | **0.37 (0.30, 0.46)** |
| 148_BAL | 0.97 (0.92, 1.03) | 0.32 (0.26, 0.40) | **0.30 (0.22, 0.38)** |
| 155_HON | 0.99 (0.94, 1.04) | **0.74 (0.66, 0.83)** | 0.74 (0.66, 0.83) |
| 158_SDG | 1.00 (0.95, 1.05) | **0.73 (0.66, 0.83)** | 0.73 (0.66, 0.83) |
| 180_ATL | 0.98 (0.93, 1.03) | 0.37 (0.33, 0.43) | **0.33 (0.26, 0.41)** |
| 183_POR | 0.99 (0.94, 1.04) | 0.39 (0.34, 0.45) | **0.38 (0.33, 0.45)** |
| 188_KW | 0.99 (0.94, 1.04) | 0.39 (0.32, 0.49) | **0.39 (0.29, 0.49)** |
| 225_KET | 0.99 (0.94, 1.05) | **0.40 (0.30, 0.50)** | 0.40 (0.30, 0.50) |
| 234_CHA | 0.98 (0.93, 1.04) | 0.37 (0.30, 0.45) | **0.36 (0.28, 0.46)** |
| 235_BOS | 0.98 (0.94, 1.04) | 0.38 (0.33, 0.43) | **0.34 (0.28, 0.41)** |
| 245_LA | 1.00 (0.95, 1.05) | **0.69 (0.60, 0.78)** | 0.69 (0.60, 0.78) |
| 246_PEN | 0.97 (0.92, 1.02) | 0.47 (0.39, 0.56) | **0.47 (0.39, 0.56)** |
| 256_JOL | 1.00 (0.95, 1.05) | **0.75 (0.66, 0.85)** | 0.75 (0.66, 0.85) |
| 265_AST | 0.96 (0.91, 1.02) | **0.44 (0.35, 0.53)** | 0.44 (0.35, 0.53) |
| 311_ANN | 0.97 (0.92, 1.03) | 0.33 (0.27, 0.40) | **0.29 (0.22, 0.38)** |
| 332_EAST | 0.99 (0.95, 1.04) | 0.34 (0.31, 0.38) | **0.30 (0.27, 0.35)** |
| 351_NEW | 0.99 (0.94, 1.03) | 0.39 (0.34, 0.46) | **0.36 (0.29, 0.45)** |
| 360_WAS | 0.96 (0.92, 1.02) | 0.37 (0.31, 0.44) | **0.36 (0.27, 0.44)** |
| 366_SAN | 0.98 (0.93, 1.03) | 0.38 (0.33, 0.44) | **0.34 (0.27, 0.42)** |
| 367_WOO | 0.98 (0.94, 1.04) | 0.39 (0.34, 0.46) | **0.36 (0.29, 0.44)** |
| 378_CRES | 0.97 (0.93, 1.03) | **0.45 (0.37, 0.54)** | 0.45 (0.37, 0.54) |
| 384_FRI | 0.97 (0.93, 1.03) | **0.43 (0.35, 0.53)** | 0.43 (0.35, 0.53) |
| 385_NEA | 0.97 (0.92, 1.03) | 0.37 (0.28, 0.47) | **0.36 (0.26, 0.47)** |
| 395_FOR | 0.98 (0.93, 1.04) | 0.37 (0.30, 0.45) | **0.36 (0.28, 0.46)** |
| 396_WIL | 0.98 (0.93, 1.04) | 0.42 (0.36, 0.51) | **0.42 (0.35, 0.52)** |
| 405_JUN | 0.99 (0.94, 1.05) | 0.54 (0.49, 0.61) | **0.47 (0.39, 0.57)** |
| 412_SOL | 0.97 (0.93, 1.03) | 0.33 (0.28, 0.39) | **0.28 (0.22, 0.37)** |
| 426_SIT | 1.00 (0.95, 1.06) | 0.43 (0.35, 0.54) | **0.41 (0.32, 0.53)** |
| 428_CED | 0.97 (0.92, 1.03) | 0.38 (0.31, 0.46) | **0.36 (0.29, 0.46)** |
| 429_NL | 0.98 (0.94, 1.04) | 0.37 (0.32, 0.43) | **0.33 (0.27, 0.41)** |
| 437_ALA | 0.99 (0.94, 1.04) | **0.60 (0.53, 0.68)** | 0.60 (0.53, 0.68) |
| 445_YAK | 0.99 (0.94, 1.05) | 0.46 (0.40, 0.54) | **0.40 (0.32, 0.50)** |
| 497_ISA | 0.96 (0.91, 1.02) | 0.40 (0.34, 0.48) | **0.39 (0.32, 0.47)** |
| 508_LUIS | 0.99 (0.95, 1.05) | **0.64 (0.56, 0.72)** | 0.64 (0.56, 0.72) |
| 519_MON | 0.98 (0.93, 1.03) | 0.38 (0.33, 0.44) | **0.33 (0.27, 0.41)** |
| 520_PET | 0.98 (0.93, 1.03) | 0.41 (0.33, 0.50) | **0.40 (0.32, 0.50)** |
| 526_GRA | 0.96 (0.91, 1.02) | 0.49 (0.44, 0.56) | **0.46 (0.39, 0.55)** |

The values in parenthesis are the 95% confidence band of the non-rejection values of d; those in bold are the estimates for the preferred model specification.

**Table 3: Estimated coefficients for the selected models**

| Series | d | $\beta_0$ | $\beta_1$ | Month AR1 |
|---|---|---|---|---|
| 10_SF | 0.58 (0.51, 0.66) | 6968.52 (180.66) | --- | 0.299 |
| 12_NY | 0.38 (0.31, 0.47) | 6912.04 (229.39) | 0.295 (4.50) | 0.401 |
| 112_FEB | 0.32 (0.24, 0.42) | 7120.09 (196.89) | 0.232 (3.09) | 0.631 |
| 127_STT | 0.42 (0.34, 0.52) | 7054.24 (187.79) | --- | 0.321 |
| 135_PHI | 0.37 (0.30, 0.46) | 6834.76 (186.85) | 0.312 (3.96) | 0.421 |
| 148_BAL | 0.30 (0.22, 0.38) | 6958.76 (249.17) | 0.281 (4.92) | 0.648 |
| 155_HON | 0.74 (0.66, 0.83) | 6994.76 (190.57) | --- | 0.263 |
| 158_SDG | 0.73 (0.66, 0.83) | 6930.84 (168.67) | --- | 0.544 |
| 180_ATL | 0.33 (0.26, 0.41) | 6898.44 (273.34) | 0.396 (7.54) | 0.430 |
| 183_POR | 0.38 (0.33, 0.45) | 7036.76 (360.68) | 0.158 (3.72) | 0.126 |
| 188_KW | 0.39 (0.29, 0.49) | 7071.00 (235.41) | 0.235 (3.55) | 0.645 |
| 225_KET | 0.40 (0.30, 0.50) | 7043.24 (208.50) | --- | 0.399 |
| 234_CHA | 0.36 (0.28, 0.46) | 6948.46 (192.78) | 0.301 (3.92) | 0.565 |
| 235_BOS | 0.34 (0.28, 0.41) | 7011.35 (387.37) | 0.241 (6.33) | 0.147 |
| 245_LA | 0.69 (0.60, 0.78) | 6964.45 (177.70) | --- | 0.522 |
| 246_PEN | 0.47 (0.39, 0.56) | 6985.20 (158.20) | 0.230 (2.07) | 0.615 |
| 256_JOL | 0.75 (0.66, 0.85) | 6903.54 (163.29) | --- | 0.525 |
| 265_AST | 0.44 (0.35, 0.53) | 6968.30 (152.90) | --- | 0.399 |
| 311_ANN | 0.29 (0.22, 0.38) | 6885.08 (268.55) | 0.325 (6.21) | 0.663 |
| 332_EAST | 0.30 (0.27, 0.35) | 6957.11 (581.35) | 0.180 (7.37) | 0.112 |
| 351_NEW | 0.36 (0.29, 0.45) | 6998.48 (345.11) | 0.259 (5.99) | 0.365 |
| 360_WAS | 0.36 (0.27, 0.44) | 6829.83 (180.31) | 0.327 (4.05) | 0.415 |
| 366_SAN | 0.34 (0.27, 0.42) | 6940.46 (273.27) | 0.365 (6.84) | 0.407 |
| 367_WOO | 0.36 (0.29, 0.44) | 6917.40 (355.40) | 0.278 (6.70) | 0.360 |
| 378_CRES | 0.45 (0.37, 0.54) | 7087.58 (199.54) | --- | 0.353 |
| 384_FRI | 0.43 (0.35, 0.53) | 7030.04 (213.89) | --- | 0.316 |
| 385_NEA | 0.36 (0.26, 0.47) | 7073.09 (170.64) | -0.175 (-1.98) | 0.472 |
| 395_FOR | 0.36 (0.28, 0.46) | 6990.50 (180.06) | 0.318 (3.84) | 0.586 |
| 396_WIL | 0.42 (0.35, 0.52) | 6988.23 (186.49) | 0.297 (3.45) | 0.313 |
| 405_JUN | 0.47 (0.39, 0.57) | 7132.96 (137.97) | -1.027 (-7.88) | 0.224 |
| 412_SOL | 0.28 (0.22, 0.37) | 6978.77 (306.59) | 0.348 (7.53) | 0.612 |
| 426_SIT | 0.41 (0.32, 0.53) | 7037.94 (159.46) | -0.172 (-1.72) | 0.436 |
| 428_CED | 0.36 (0.29, 0.46) | 6934.56 (230.15) | 0.212 (3.29) | 0.700 |
| 429_NL | 0.33 (0.27, 0.41) | 6949.22 (356.43) | 0.254 (6.26) | 0.394 |
| 437_ALA | 0.60 (0.53, 0.68) | 7001.56 (178.94) | --- | 0.273 |
| 445_YAK | 0.40 (0.32, 0.50) | 7025.33 (152.11) | -0.684 (-6.63) | 0.447 |
| 497_ISA | 0.39 (0.32, 0.47) | 6934.30 (185.98) | 0.354 (4.31) | 0.616 |
| 508_LUIS | 0.64 (0.56, 0.72) | 6969.98 (180.63) | --- | 0.506 |
| 519_MON | 0.33 (0.27, 0.41) | 6992.81 (365.32) | 0.302 (7.61) | 0.380 |
| 520_PET | 0.40 (0.32, 0.50) | 7005.62 (228.36) | 0.256 (3.75) | 0.667 |
| 526_GRA | 0.46 (0.39, 0.55) | 6735.09 (155.02) | 0.745 (6.95) | 0.620 |

The values in parenthesis in the third and fourth columns refer to the corresponding t-values; values higher than 1.64 indicate significance of the estimated coefficients.

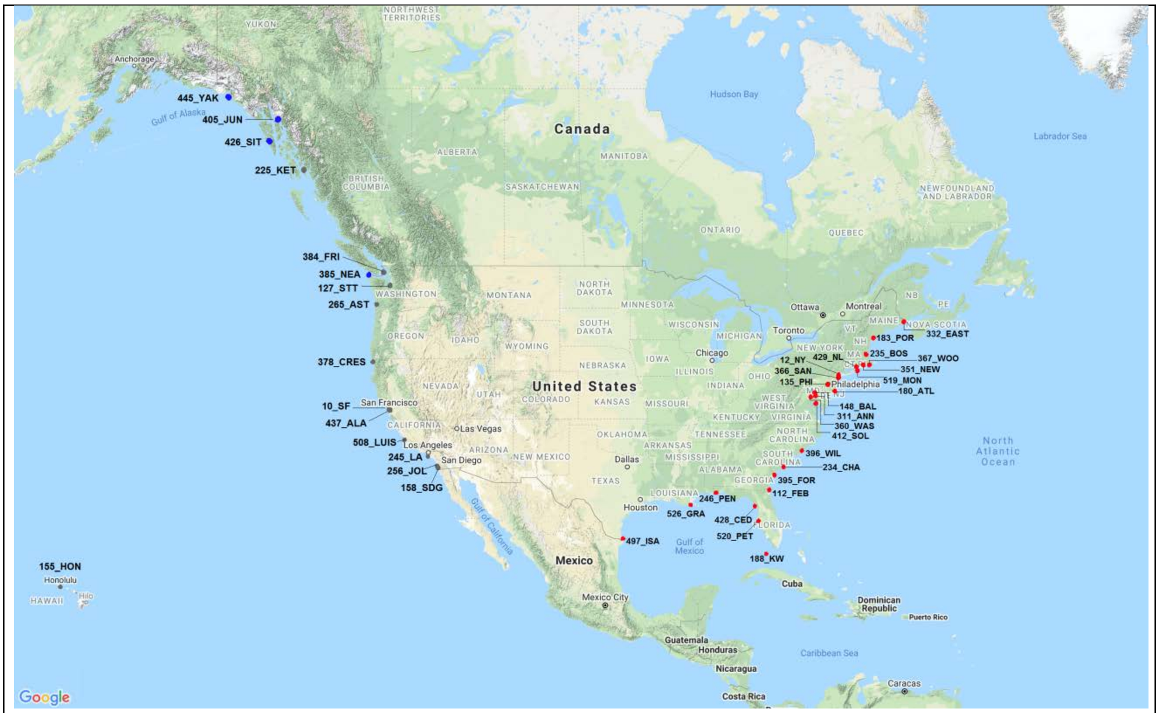
**Table 4: Classification based on the time trend coefficient**

| Significant negative time trend | | Insignificant time trend | Significant positive time trend | |
|---|---|---|---|---|
| 405_JUN | (-1.027) | 10_SF | 183_POR | (0.158) |
| 445_YAK | (-0.684) | 127_STT | 332_EAST | (0.180) |
| 385_NEA | (-0.175) | 155_HON | 428_CED | (0.212) |
| 426_SIT | (-0.172) | 158_SDG | 246_PEN | (0.230) |
| | | 225_KET | 112_FEB | (0.232) |
| | | 245_LA | 188_KW | (0.235) |
| | | 256_JOL | 235_BOS | (0.241) |
| | | 265_AST | 429_NL | (0.254) |
| | | 378_CRES | 520_PET | (0.256) |
| | | 384_FRI | 351_NEW | (0.259) |
| | | 437_ALA | 367_WOO | (0.278) |
| | | 508_LUIS | 148_BAL | (0.281) |
| | | | 12_NY | (0.295) |
| | | | 396_WIL | (0.297) |
| | | | 234_CHA | (0.301) |
| | | | 519_MON | (0.302) |
| | | | 135_PHI | (0.312) |
| | | | 395_FOR | (0.318) |
| | | | 311_ANN | (0.325) |
| | | | 360_WAS | (0.327) |
| | | | 412_SOL | (0.348) |
| | | | 497_ISA | (0.354) |
| | | | 366_SAN | (0.365) |
| | | | 180_ATL | (0.396) |
| | | | 526_GRA | (0.745) |

**Table 5: Classification based on persistence**

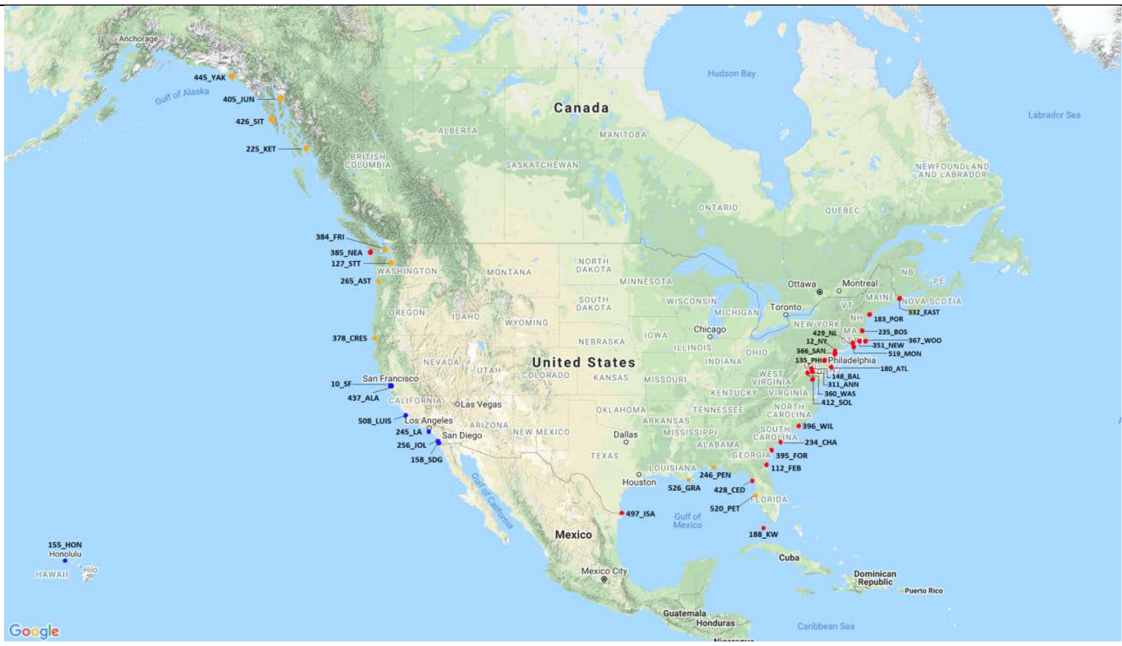
| **$0 < d < 0.5$ Stationarity** | | **$0 < d < 1$** | | **$0.5 \leq d < 1$ Non-stationarity** | |
|---|---|---|---|---|---|
| 412_SOL | (0.28) | 225_KET | (0.40) | 10_SF | (0.58) |
| 311_ANN | (0.29) | 445_YAK | (0.40) | 437_ALA | (0.60) |
| 148_BAL | (0.30) | 520_PET | (0.40) | 508_LUIS | (0.64) |
| 332_EAST | (0.30) | 426_SIT | (0.41) | 245_LA | (0.69) |
| 112_FEB | (0.32) | 127_STT | (0.42) | 158_SDG | (0.73) |
| 180_ATL | (0.33) | 396_WIL | (0.42) | 155_HON | (0.74) |
| 429_NL | (0.33) | 384_FRI | (0.43) | 256_JOL | (0.75) |
| 519_MON | (0.33) | 265_AST | (0.44) | | |
| 366_SAN | (0.34) | 378_CRES | (0.45) | | |
| 235_BOS | (0.34) | 526_GRA | (0.46) | | |
| 385_NEA | (0.36) | 246_PEN | (0.47) | | |
| 360_WAS | (0.36) | 405_JUN | (0.47) | | |
| 234_CHA | (0.36) | | | | |
| 395_FOR | (0.36) | | | | |
| 367_WOO | (0.36) | | | | |
| 351_NEW | (0.36) | | | | |
| 428_CED | (0.36) | | | | |
| 135_PHI | (0.37) | | | | |
| 12_NY | (0.38) | | | | |
| 183_POR | (0.38) | | | | |
| 188_KW | (0.39) | | | | |
| 497_ISA | (0.39) | | | | |

**Figure 1:** Time trend coefficients. Summary of data extracted from Table 4.




• Significant positive time trend; • Insignificant time trend; •Significant negative time trend.

**Figure 2:** Degree of persistence. Summary of data extracted from Table 5.




• $d < 0.4$; • $0.40 \leq d < 0.5$; • $d > 0.5$.